LONG-HORIZON STOCK RETURNS PREDICTABILITY:
EVIDENCE FROM THE STOCK EXCHANGE OF THAILAND

Suthawan Prukumpai

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ABSTRACT

Title of Dissertation  Long-Horizon Stock Returns Predictability: Evidence from the Stock Exchange of Thailand
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The primary purpose of this dissertation is to investigate the behavior of the stock returns over long horizons using the data from the Stock Exchange of Thailand. In Chapter 2, the long-run relationship between stock prices and dividends is investigated. The null hypothesis of no cointegration using both the Engle-Granger and Johansen cointegration tests cannot be rejected; however, when the structural break is addressed, the Gregory-Hansen cointegration test reports the significant evidence of the long-run relationship between stock prices and dividends.

Chapter 3 explores the evidence of structural break in dividend-price ratio. The Bai and Perron’s (1998) structural break test shows that there is one break located on October 1986. The results show that the long-horizon returns predictability is strong and increasing over time horizons. Moreover, the information of structural break both in mean of predictor and in cointegrating relationship is important and hence should not be ignored. These findings explain the weak evidence of return predictability in past literatures, in which those models were misspecified.

Chapter 4 further examines the relationship between stock prices and dividends in VAR and VECM. The issue of permanent and transitory components in stock prices and dividends has been emphasized in particular. Interestingly, the results from IRFs show that the effect of price shock is dried out quickly over time while that of dividend shock is not. These imply that the price shock has temporary effect whereas the dividend shock has permanent effect. In addition, the results from VD provide evidence that most of fluctuation in stock prices can be explained by their own innovation. In other words, the stock prices move according to price shocks or discount rate shocks similar to those reported in Cochrane (1994, 2011). In summary, stock prices gradually revert back to their long-term equilibrium and dividends are unpredictable.
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CHAPTER 1

INTRODUCTION TO LONG-HORIZON STOCK RETURNS
PREDICTIVE REGRESSION

1.1 Introduction

An attempt to predict stock market returns is one of the most interesting issues in asset pricing. Investors are usually fascinated about how to forecast future stock prices to earn enormous returns from the stock market. For financial economists, stock return predictability has received substantial attention because of its implications for financial models of risk and return. Fama and French (1988) and Lo and MacKinlay (1988) provide supporting evidence that stock prices do not follow a random-walk process, especially in long horizon. They suggest that stock price movement can be explained by a mean reversion process at least in some components. Therefore, the recent view in finance is that the evidence for long-horizon stock return predictability is significantly stronger than that for short horizons. Moreover, the underlying factor of long-horizon returns predictability is time-varying expected returns (or time-varying discount rate). Specifically, the returns predictability phenomenon occurs over an economic cycle and a longer horizon (Cochrane, 1999). Further, it is the expected that return on individual securities as well as the market as a whole vary slowly over time will represent the changing individuals’ risk aversion over time in each economic condition. This is the dominant view on returns predictability in the finance profession at present. Therefore, it is worth nothing to consider the possibility that returns predictability may result from an inefficient market. Yet, in spite of substantial theoretical and empirical support for long-horizon returns predictability, the empirical literature has recently become aware of serious statistical problems that affect long-horizon study.
1.2 Motivation

This dissertation was inspired by the “New Fact in Finance” paper by Cochrane (1999) and by the emergence of forecasting techniques in recent literature. It is well accepted that evidence of returns predictability does not overturn the views of an efficient market. Instead, it has shifted from the constant expected return paradigm to the time-varying expected return. Therefore, it does enlarge our understanding of asset pricing theory and it also challenges our view about risk premium (expected returns) over time.

1.3 Problem Statement

The stock returns predictability literature has also been extensively studied based on U.S. data and some developed countries in Europe; however, studies of returns predictability in emerging countries are few and far from complete. Among emerging countries in Southeast Asia, the Stock Exchange of Thailand (SET) has been established and well developed since 1975. The market size together with the economic growth have attracted foreign investors’ and institutional investors’ interest. Therefore, the evidence of return predictability from Thailand would add to empirical evidence from outside the U.S.

The main objective of this dissertation is to investigate the behavior of stock returns in long horizons. Evidence of time-varying expected returns in Thailand since the opening of the stock exchange will be explored. Unlike most studies which are largely focused on short-horizon returns predictability with the objective of creating trading strategy to exploit short-run profit, this study is conducted to fill in literature gap as a main purpose. In particular, rather than answering how we can make a profit from predictability of stock returns, the problems related to returns predictive regression and how to mitigate such problems will be investigated. Therefore, the main research question can be stated as:

What is the evidence of long-horizon stock returns predictability in Thailand?

To examine this, the present value model of stock prices under time-varying expected returns developed by Campbell and Shiller (1988) is used as the framework.
Due to the data availability together with the aim of making the results comparable to previous literature, the most popular predictor, the dividend-price ratio in particular, was then chosen.

To answer the main research question, the existence of cointegration relationship is tested and the predictive regression is estimated using both stock return and dividend growth as dependent variables. Next, the issue of model instability or structural break is carefully considered since the data covered long span of time and then the proper adjustment methods are drawn in order to take account for the presence of the structural break. Finally, this dissertation is aim to explore the predictability in the multivariate framework using the VAR model. The VAR framework provides information about the response of stock prices and dividend to shocks. In addition, the short-run dynamic and long-term behaviors of stock prices are investigated.

1.4 Contributions

According to the limited literature in this area using emerging market data, to my knowledge, this is the first study in Thailand to investigate the stock returns predictability in the long horizon. Moreover, this is a comprehensive study of predictability regarding returns and dividend growth. According to Cochrane (2008), evidence of the unpredictability of dividend growth provides substantial indirect support of return predictability. Therefore, rather than focusing only on long-horizon returns predictability, it is of interest to examine the extent to which dividend growth can be predicted.

The empirical results from this study have contributed significantly as follows. Firstly, it showed strong positive evidence that over the long-horizon, stock prices in Thailand were linked to fundamentals and predictability of stock returns over long-horizon was also found. Secondly, the presence of structural break was not only able to explain the failure to detect the cointegration relationship in the previous studies but also raised a caution for further research to employ proper econometric methodology. Lastly, the limitation of empirical evidence from markets outside U.S. and some developed countries could be filled by this study.
1.5 Theoretical Framework

The purpose of this chapter is to present the concept of constant and time-varying expected returns as well as the present value model of stock prices. Although this is not the main purpose of this dissertation, it is worth briefly discussing predictability and the efficient-market hypothesis. The details are mainly drawn from Campbell, Lo, and MacKinlay (1996) and Cochrane (2005).

1.5.1 Present Value Model of Stock Price under Constant Expected Returns

The definition of the simple return on dividend-paying stock between time $t$ and $t+1$ can be written as,

$$R_{t+1} = \frac{P_{t+1} + D_{t+1} - P_t}{P_t},$$

or

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} - 1, \quad (1.1)$$

where $P_t$ is the stock price at time $t$ and $D_t$ is the dividend paid over period $t$. By taking conditional expectation on the information at time $t$ to equation (1.1), the current price can be expressed as an expected sum of the next period price and dividend, discounted with returns $R_{t+1}$.

$$E_t(P_{t+1}) = P_t = \frac{E_t[P_{t+1} + D_{t+1}]}{E_t[1 + R_{t+1}]]. \quad (1.2)$$

Assume that expected return is constant over time and expected dividend is equal to zero, i.e. $E_t[D_{t+1}] = 0$. Therefore, the stock price follows a martingale or random walk model,

$$P_t = E_t[P_{t+1}], \quad (1.3)$$

or

$$P_{t+1} = P_t + \epsilon_{t+1}. \quad (1.4)$$
Under the efficient-market hypothesis, it is often thought that the price observed today is the best predictor of tomorrow’s price\(^1\). In other words, it implies that market prices are rational and hence \( \delta_{t+1} = \mathbb{E}_t[P_{t+1}] - P_{t+1} \) will be unpredictable based on the information at time \( t \). In addition, if price is a martingale, returns, \( R_{t+1} = P_{t+1} - P_t \), must be a fair game\(^2\), such that the fair game implies that on average the abnormal return is zero, \( \mathbb{E}_t[R_{t+1}] = \mathbb{E}[P_{t+1} - P_t] = 0 \). Specifically, an investor may experience excess profits or losses in some periods, but these average out to zero over time. Notably, this interpretation is based on the assumptions that expected return is constant and expected dividend is zero. However, the fact that expected dividend is equal to zero is only valid for very short periods and does not hold true, especially in a long-horizon framework.

Instead of assuming the constant expected returns equal to zero, if we now assume that expected dividend is zero and expected return is constant but greater than zero, \( \mathbb{E}_t[R_{t+1}] = R > 0 \). Solving equation (1.2) forward, price will follow a sub-martingale process,

\[
\mathbb{E}[P_{t+1}] = (1 + R)P_t, \tag{1.5}
\]

Again, under this assumption, the deviation of the constant expected return, \( \mathbb{E}_t[R_{t+1} - R] = 0 \), or abnormal return, is still a fair game.

Now, consider the dividend-paying stock with the assumption that \( \mathbb{E}_t[R_{t+1}] = R > 0 \). Using equation (1.2) and the above assumption, the Euler equation that determines the change in price over time can be expressed as,

\[
P_t = \delta \mathbb{E}_t[P_{t+1} + D_{t+1}], \tag{1.6}
\]

where \( \delta \) represents a discount factor which is equal to \( \frac{1}{1 + R} \) and \( 0 < \delta < 1 \). Therefore, the one-period future price can be written as,

\[
P_{t+1} = \delta \mathbb{E}_{t+1}[P_{t+2} + D_{t+2}]. \tag{1.7}
\]

---

\(^1\) This is a property of the martingale process. Specifically, suppose a stochastic variable \( X \) has the following property; \( \mathbb{E}_t[X_j] = X_t \), where \( \Omega_t \) is information set at time \( t \). Then \( X_t \) is said to be a martingale since the best forecast of all future values of \( X_j \) \((j \geq 1)\) is the current value \( X_t \).

\(^2\) A fair game has the property of zero expectation. Specifically, a stochastic process \( X \) is a fair game if \( \mathbb{E}_t[X_{t+1} | \Omega_t] = 0 \). Sometimes, a fair game is referred to as a martingale difference.
If taking conditional expectation at time $t$ to equation (1.7), according the Law of Iterated Expectations$^3$, equation (1.7) can be shown as

$$E_t[P_{t+1}] = \delta E_t[P_{t+2} + D_{t+2}].$$

Equation (1.8) implies that the today’s expectation of tomorrow price is equal to today's expectation of the next two-day price. This is consistent with the rational expectation (RE) since you cannot alter your expectations in the future. Equation (1.8) holds for all periods so that,

$$E_t[P_{t+2}] = \delta E_t[P_{t+3} + D_{t+3}].$$

Next, substitute equation (1.8) into equation (1.6), and successive substitute to $N$-period,

$$P_t = \delta (\delta E_t[P_{t+2} + D_{t+2}]) + \delta E_t[D_{t+2}],$$

$$P_t = \delta^2 (\delta E_t[P_{t+3} + D_{t+3}]) + \delta^2 E_t[D_{t+3}] + \delta E_t[D_{t+2}],$$

$$P_t = \delta^N (E_t[P_{t+N} + D_{t+N}]) + E_t[\delta D_{t+1} + \delta^2 D_{t+2} + \cdots + \delta^N D_{t+N}].$$

(1.9)

Now let $N \to \infty$ then $\delta^N \to 0$, therefore

$$\lim_{N \to \infty} \delta^N (E_t[P_{t+N} + D_{t+N}]) \to 0.$$  

(1.10)

Notably, equation (1.10) is known as a terminal condition or transversality condition, and it rules out the rational bubbles. Equation (1.9) then becomes,

$$P_t = E_t[\delta D_{t+1} + \delta^2 D_{t+2} + \cdots + \delta^N D_{t+N}] = E_t \sum_{i=1}^{N} \delta^i D_{t+i}. $$

(1.11)

The equation (1.11) is derived under the assumptions that the expected returns is constant, and it implies that the rational current price should be equal to the discounted present value of expected future dividends such that if the observed current price is not equal to the rational price, an unexploited profit opportunity exists in the market. Typically, this equation refers to the present value model of stock under a constant discount rate$^4$. According to equation (1.11), Engsted (2006) notes that the predictability of future dividends implies the predictability of stock prices. Since the

---

$^3$ Law of Iterated Expectation: $E_t[E_{t+1}(X_{t+1})] = E_t(X_{t+1})$

$^4$ Some textbooks and studies refer to it as a rational valuation formula (RVF).
predictability of future dividend does not conflict with the efficient market hypothesis, the abnormal returns are still unpredictable and the efficient market hypothesis is not violated.

1.5.2 Present Value Model of Stock Price under Time-Varying Expected Returns

Recent empirical studies have shown that expected returns are not constant over time (e.g. Fama and French, 1988; Cochrane, 1999). In particular, investors require different expected returns in each future period so that they can willingly hold a particular risky asset. Therefore, the assumption of constant expected return is relaxed and Campbell and Shiller (1988) derive the present value model of stock prices in a context of time-varying expected returns. Recall equation (1.1) and state it in logarithm form as

\[
\ln(P_{t+1} + 1) = \ln \left( \frac{P_{t+1} + D_{t+1}}{P_t} \right) = \ln(P_{t+1} + D_{t+1}) - \ln(P_t).
\]  

(1.12)

Rewrite \( \frac{P_{t+1} + D_{t+1}}{P_t} \) as \( \frac{P_{t+1}}{P_t} \cdot \frac{1 + D_{t+1}}{P_{t+1}} \), then take logarithm to get

\[
\ln \left( \frac{P_{t+1}}{P_t} \right) \cdot \ln \left( \frac{1 + D_{t+1}}{P_{t+1}} \right) = \ln \left( \frac{P_{t+1}}{P_t} \right) + \ln \left( 1 + \frac{D_{t+1}}{P_{t+1}} \right) + \ln(P_{t+1}).
\]

Therefore, equation (1.12) becomes

\[
\ln(P_{t+1} + 1) = \ln \left( 1 + \frac{D_{t+1}}{P_{t+1}} \right) + \ln(P_{t+1}) - \ln(P_t).
\]  

(1.13)

If lower-case letters denote logarithm, then equation (1.13) can be expressed as

\[
\tilde{r}_{t+1} = \ln \left( 1 + \exp \left( \frac{d_{t+1} - \tilde{p}_{t+1}}{} \right) \right) + \tilde{p}_{t+1} - \tilde{p}_t
\]  

(1.14)

Note that the first term in equation (1.14) is nonlinear function in \( d_{t+1} \) and \( \tilde{p}_{t+1} \). The nonlinearity of equation (1.14) makes it difficult to handle and means that the simple time-series tools cannot be used. However, following Campbell and Shiller (1988), the linearization of equation (1.14) can be obtained by taking a first-order Taylor series expansion around the mean of \( p \) and \( d \). Like any nonlinear function, \( f(x_{t+1}) \), it can be approximated around its mean \( (\bar{x}) \), using a first-order Taylor expansion:

\[
f(x_{t+1}) \approx f(\bar{x}) + f'(\bar{x})(x_{t+1} - \bar{x}).
\]
Hence, a first-order Taylor expansion of equation (1.14) is

\[ r_{t+1} \approx k + \rho r_{t+1} + (1 - \rho) \Delta d_{t+1} - p_c, \]

where \( \rho \) and \( k \) are parameters of linearization defined by

\[ \rho \equiv 1f(1 + \exp \left( \frac{d}{a - p} \right)), \]

and where \( \bar{d} - \bar{p} \) is the average log dividend-price ratio and

\[ k \equiv -\ln(\rho) - (1 - \rho) \ln(1/\rho - 1). \]

Notice that the log of the sum of prices and dividend in equation (1.12) is replaced by the Taylor approximation with a weighted average of the log of prices and log of dividend in equation (1.15). In particular, the log of price gets weight of \( \rho \) while the log of dividend gets weight of \( (1 - \rho) \). Equation (1.15) is a linear difference equation for the log of prices under the time-varying expected return condition. The accuracy of such an approximation depends on the constancy of the log dividend-price ratio. To be more specific, when \( \Delta d_{t+1} \) and \( p_{t+1} \) move together one-by-one, equation (1.15) is equivalent to equation (1.14).

By adding and subtracting \( d_t \) in equation (1.15) and assuming a constancy of the log dividend-price ratio or assuming \( \Delta d_{t+1} \) and \( p_{t+1} \) move together one-by-one, it becomes

\[ r_{t+1} = k + \rho r_{t+1} + (1 - \rho) \Delta d_{t+1} - p_t + d_t - d_t, \]

\[ r_{t+1} = k + \Delta d_{t+1} - d_t + (d_t - p_t) - \rho (d_{t+1} - p_{t+1}), \]

\[ r_{t+1} = k + \Delta d_{t+1} + \Delta p_t - \rho \Delta p_{t+1} \]

(1.16)

where \( \Delta d_{t+1} \) denotes dividend growth and \( \Delta p_t \) denotes log dividend-price ratio.

Equation (1.16) can be rewritten in terms of log dividend-price ratio as follows:

\[ \Delta p_t = -k + \rho \Delta d_{t+1} + r_{t+1} - \Delta d_{t+1}. \]

If equation (1.17) is solved forward and a transversality condition is imposed, it becomes

\[ \Delta p_t = \sum_{j=0}^{\infty} \rho^j (r_{t+f+1} - \Delta d_{t+f+1}) - \frac{k}{1 - \rho}. \]

(1.18)

In word, equation (1.18) states that the log dividend-price ratio is a discounted sum of all future returns minus the discounted sum of all future dividend growth less a constant term. The ex-ante version of equation (1.18) can be obtained by taking conditional expectation with information at time \( t \) on both sides, and equation (1.19) is obtained. Therefore, log dividend-price ratio is high when dividends are expected to grow at a slow rate or when stock returns are expected to be high.
Interestingly, equation (1.19) is analogous to the Gordon Growth model, 
\[
\frac{p_t}{g} = r - g,
\]
where \( r \) and \( g \) denote rate of returns and dividend growth rate. Campbell and Shiller (1988) call it the dynamic Gordon Growth model. Likewise, the equation (1.19) can be written in terms of price to represent the present value the model of stock prices.

\[
p_t = \sum_{j=0}^{\infty} \rho^j (E_t[1 + d_{t+j+1}] - E_t[r_{t+j+1}]) - \frac{k}{(1 - \rho)}
\]

(1.19)

Interestingly, equation (1.19) is analogous to the Gordon Growth model, 
\[
\frac{p_t}{g} = r - g,
\]
where \( r \) and \( g \) denote rate of returns and dividend growth rate. Campbell and Shiller (1988) call it the dynamic Gordon Growth model. Likewise, the equation (1.19) can be written in terms of price to represent the present value the model of stock prices.

Similarly, equation (1.20) is a dynamic version of the Gordon Growth model, 
\[
\frac{p_t}{g} = \frac{p_t}{r - g}.
\]
Like the original version, equation (1.20) states that stock prices are high when dividends are expected to grow rapidly or when dividends are discounted at a lower rate. Unlike the original model, the dynamic version allows dividend growth and expected returns to vary from period to period. Consequently, the log dividend-price ratio must also vary. Put another way, if the log dividend-price ratio varies over time in the real data, then from equation (1.19), it must forecast either future dividend growth or future expected returns or both.

In conclusion, under the constant expected returns, the abnormal returns are still unpredictable and the efficient-market hypothesis (under Fama’s (1970) view) is not violated. However, if the expected return is time-varying, the predictability of returns is possible. Cochrane (2005) summaries that return predictability is another side of the same coin regarding the existence of time-varying expected returns.

1.6 Literature Review

1.6.1 Efficient-Market Hypothesis and Time-Varying Expected Returns

Predictability of stock returns is a very broad field with a long history and is a very active research topic. It is impossible to provide a complete survey of this huge literature in just a few pages. Hence, the most cited works which shed light on this area are picked up and recent empirical works are mainly focused.
Originally, testing for predictability of stock return was motivated by the efficient-market hypothesis, which provides one of the richest branches of literature in empirical asset pricing. Fama (1970, 1991) states that financial markets are efficient with respect to particular information set when prices fully reflect all relevant and available information. Since market prices already contain most updated information about fundamental value and, because the business of discovering information about the value of traded assets is extremely competitive, there is no easy way to make a profit. The only way to earn higher returns is by taking on additional risk. In sum, according to Fama’s (1970) view, the stock price is a random-walk process and hence no one can predict the changes in future prices. Technically, under the random-walk hypothesis, the autocorrelations are zero.

Lo and MacKinlay (1988) examined the autocorrelations in individual stock returns over several horizons, daily, weekly, and monthly in particular, and found that the daily autocorrelations were positive and significant at the first lag over the entire sample. A similar pattern was found for weekly and monthly returns. Even weekly and monthly return autocorrelations were positive and significant at the first lag; the subsequent lags had smaller sizes and sometimes show negative higher-order autocorrelations. Fama and French (1988) also used variance ratios to test the random-walk hypothesis of stock returns. They found evidence against the random-walk hypothesis since the variance ratios were greater than one, which implies the positive autocorrelations of returns. However, they found that there were weak negative autocorrelations, indicated by variance ratios of less than one for weekly and monthly returns. In addition, they ran a univariate regression of long-horizon returns on past long-horizon returns and found negative and significant estimated coefficients. They simply concluded that a series of good past returns forecasts bad future returns. In contrast to Lo and MacKinlay (1988), who found negative autocorrelations in individual stock returns, Fama and French (1988) found negative autocorrelation in multi-year index returns. Specifically, they explored U.S. data from 1926 to 1985 and found large negative autocorrelations for the return horizon over a year. They also concluded that such negative autocorrelations were induced by slowly mean reverting component of stock price. Therefore, the predictability of return is possible for 3 – 5 years returns. Summers (1986) also confirms that returns in long
horizons exhibit negative autocorrelations as reflected in the values of variance ratios less than a unity. In addition, Poterba and Summers (1988) have provided an explanation of the permanent and transitory (or temporary in Fama and French, 1988) of stock prices. Specifically, they argue that mean-reverting behavior in stock prices is consistent with transitory deviations from an equilibrium and hence imply a positive autocorrelation in short horizon returns and a negative autocorrelation over longer horizons.

The early evidence of the random-walk hypothesis using short-horizon returns was hardly rejected and hence the return was not predictable. This finding was consistent with the efficient-market hypothesis under the constant expected returns framework and was widely accepted that any apparently predictability either resulted from a statistical artifact which quickly vanished out of the sample or could not be exploited after transaction costs. Moreover, any empirical evidence indicating predictability in stock returns was firstly interpreted as evidence of an inefficient market (Summers, 1986). However, once the stock returns predictability has been employed in the long-horizon framework, the evidence that stock prices depart from the random-walk hypothesis increases.

Ball and Kothari (1989) cast doubt on the anomalous nature of negative autocorrelation in long-horizon returns; they find that such negative autocorrelation is due almost entirely to variation in relative risks, and thus expected returns through time. Fama and French (1989) come up with an intuitive explanation which provides a systematic relationship between expected returns and business conditions. Specifically, they argue that such predictability results from the time-varying of expected returns over time. They suggest that when economic conditions are strong, expected returns are low and vice versa. In addition, they provide empirical evidence to support the idea that the dividend-price ratio captures the variation in economic conditions. Specifically, they show that dividend-price ratio forecasts high returns when economic conditions are weak and low returns when economic conditions are strong. They wisely interpret such findings relative to the consumption smoothing which is a common feature of the Intertemporal asset-pricing model (e.g. Merton, 1973). More typically, the consumption smoothing models predict that expected returns vary opposite to business conditions. Furthermore, they conclude that the dividend-price ratio is a proper proxy of risk in each economic condition.
Among works, the article “New Fact in Finance” by Cochrane (1999) provides a comprehensive survey of the different views regarding financial economics. Unlike the 1980’s view, he points out that all new facts are based on the same theme; the time-varying expected returns. One of the stylized facts summarized by Cochrane (1999) is that returns are predictable in long horizons. Subsequently, the hypothesis of returns predictability is typically referred to as a new fact in finance. In order to emphasize the importance of time-varying expected returns, Cochrane (1999) mentions that

These views are not ideological or doctrinaire beliefs…. The new findings do not overturn the cherished view that markets are reasonably competitive and, therefore, reasonable efficiency. However, they do substantially enlarge our view of what activities provide reward for holding risks and they also challenge our understanding of those risk premiums.

In addition, his presidential address in the American Finance Association 2010 emphasizes that

Discount rate variation [time-varying expected return] is the central organizing question of current asset-pricing research… Previously, we thought returns were unpredictable, with variation in price-dividend ratios due to variable in expected cash flows. Now it seems all price-dividend variation corresponds to discount rate variation.

His argument had been a 100% reversal in academic thinking in the past 30 years, where expected returns are not any longer constant over time and the all time-variation in valuation ratios was once thought to reflect changing growth expectation (changing in future cash flows); now all such variations reflect changing expected returns.

Recently, a number of models have been proposed to explain the time-varying behavior of expected returns. Campbell and Cochrane (1999) for example introduce a habit formation model in which people have developed habits for consumption levels
such that the utility of consuming today depends on how much they usually consume. The habit formation model predicts that investor increases risk aversion level as consumption drops due to a bad economy and consumes close to the habit level of consumption, while in the good times, the consumption is above the habit level and hence risk aversion decreases. Thus, risk aversion varies with economic conditions and this leads to time-varying expected returns.

Engsted (2006) provides the insight that if expected returns are constant, then the variations in price or abnormal returns are unpredictable and hence consistent with the traditional efficient market hypothesis view. However, if expected returns are time-varying, returns are predictable by variables that track the economic conditions; and such predictability evidence does not invalidate the prominence of the traditional efficient-market hypothesis view since it is based on a different perspective. Specifically, if the time-varying expected returns are accepted, the evidence of predictability is a positive interpretation. Therefore, it is not the intention of this dissertation to argue for or against the notion of market efficiency. Instead, the time-series property of stock prices and returns is mainly focused since the issue itself has important implications.

### 1.6.2 Long Horizons Returns

Using short-horizon returns, daily or weekly, early studies generally found that returns are unpredictable since the autocorrelations in returns are insignificant. The empirical findings of negative autocorrelations in long horizons (e.g. Fama and French, 1988; Lo and MacKinlay, 1988; Poterba and Summers, 1988) have motivated several studies that focus on the properties of long horizon returns. Muth (1960) first proposes the hypothesis that stock prices comprise two components; a random walk $(w_t)$ and a stationary process $(y_t)$,

$$
\begin{align*}
  p_t &= w_t + y_t, \\
  w_t &= \mu + w_{t-1} + \epsilon_t; \quad \epsilon_t \sim iid (0, \sigma^2).
\end{align*}
$$

Equation (1.21) indicates that stock prices consist of a fundamental component $(w_t)$ that reflects equilibrium price and a stationary component $(y_t)$ that reflects a short term deviation from the equilibrium price. He shows that stock prices may take long temporary swings from their fundamental value (permanent component) and slowly mean-revert to the fundamental value. To be more specific, suppose that there
is a positive stationary shock to the current stock price. One would expect the current stock price to rise above what it should be in absence of such shock; hence the current stock returns would greater than the long run mean. Since the stationary shock is expected to fade away in the long run, stock prices will decline to their normal levels, which are dominated mainly by the permanent component. This will induce the negative autocorrelation in long-term stock returns. However, the slowly-decaying temporary component which introduces a negative autocorrelation in returns is difficult to detect in short-horizon returns.

To test the autocorrelations in a long horizon, if the horizons are long enough, the variance ratios must less than one. However, there is only weak evidence for the predictability of long horizon returns given past stock returns. With extensive empirical studies of returns predictability (under time-varying assumption), Campbell and Shiller (1988) provide a theoretical model to relate the valuation ratio to the return predictability, as discussed in Section 1.5.2. Rather than using past returns, recently studies have used many predictors. Popular predictors include the dividend-price ratio (see e.g. Campbell and Shiller, 1988, 2001, Campbell, 1991; Cochrane, 1992, 1994, 2005; Welch and Goyal, 2008), the price earnings ratio (see e.g. Campbell and Shiller, 1988; Lamont (1998); Rapach, Wohar, and Rangvid, 2005; Welch and Goyal, 2008), and price-output ratio (Rangvid, 2006). The ability to predict returns is not limited to the valuation ratio. Around the same time, several papers pointed out that yields spread on treasury and corporate bonds can also be correlated with returns (Fama and Schwert, 1977; Campbell, 1987; Fama and French, 1989). Some macroeconomic variables are also able to predict returns, i.e. the output gap (Cooper and Priestley, 2009), the consumption-wealth ratio or $cay$ (Lettau and Ludvigson, 2001), and the consumption-dividend ratio or $cdy$ (Lettau and Ludvigson, 2005).

Campbell and Shiller (2001) and Cochrane (2005) also showed that the long-run coefficient is a more powerful statistic than the short-run coefficient. Suppose that $r$ is the returns and $x$ is any state variable or predictor,

\begin{align}
  r_{t+1} &= \delta x_t + s_{t+1,}\quad (1.22) \\
  x_{t+1} &= \phi x_t + \delta_{t+1}. \quad (1.23)
\end{align}

Assuming that the predictor follows an AR(1) process, the two-year return predictive regression is
Then substituting equation (1.23) into equation (1.24) and work forward to N-horizon, equation (1.24) becomes

$$r_{t+1} + r_{t+2} + \ldots + r_{t+N} = b(1 + \phi + \phi^2 + \ldots + \phi^{N-1})x_z + \text{error}. \quad (1.25)$$

As can be seen from the above equations, a central fact driving the predictability of returns is that the state variable is very persistent ($\phi$ is large and near one). Equivalently, if daily returns are very slightly predictable by a slow-moving variable, that predictability adds up over long horizons.

### 1.6.3 Long Horizons Predictive Regression

Recall equation (1.19), which states that given that log dividend-price ratio varies over time in the real data, the log dividend-price ratio must forecast either future dividend growth or future expected return or both. Despite the fact that dividend-price ratio should be used to predict both stock returns and dividend growth, most studies focus on return predictability. A concurrent line of research has confirmed the absence of dividend growth predictability and the economic importance of the variability in expected return (Campbell and Shiller, 1988; Lamont, 1998; Campbell, 1991; Campbell and Shiller, 2001).

The most cited work by Cochrane (2005), which estimates both returns and dividend growth predictive regressions in the long horizon, shows evidence to support returns predictability. Specifically, Cochrane (2005: 392) updates the table in Fama and French (1988) and precisely concludes that at longer and longer horizons larger and larger fractions of return variation are forecastable. In addition, the coefficients in the dividend growth case are much smaller and $R^2$ is tiny. Worse, the signs are all wrong. Even moving to the Vector Autoregression (VAR) framework, Cochrane (2008) challenges that something (dividend growth, in particular) should be predictable so that returns are not predictable. Instead he finds that dividend growth is nearly unpredictable. His concreted study concludes that prices indeed reveal expected returns. If expected returns rise, prices are driven down since future dividends or other cash flows are discounted with a higher rate. A low price then reveals a market expectation of a high expected or required return. This is true in bad
economy, such that, the expected return is time-varying and varies slowly over time. Thus, we can track market expectations of returns by looking at the dividend-price ratio.

Even though there are positive evidences of stock returns predictability, there is growing evidence supporting dividend growth predictability, especially when using U.S. data before the Second World War (Chen, 2009) or testing non-U.S. data (see e.g., Engsted and Pedersen, 2010 and Rangvid, Schmeling, and Schrimpf, 2011). Chen (2009) challenged this “stylized fact” by showing that for the period up to the end of the Second World War, the opposite predictability pattern characterized the U.S. stock market. Dividend growth was strongly predictable during from 1872 to 1945 but it completely disappeared during the Second World War, in particular.

Overall, the huge evidence supporting return predictability, while dividend growth is not, has been interpreted as almost all variation in dividend-price ratio is due to changing expectations about future returns (or expected returns), whereas changing expectations about future dividends playing no role. Nevertheless, increasing evidence on dividend growth predictability has raised an interesting paradox since the conclusion regarding such findings may overturn the perception about predictability. Therefore, to answer these questions, a comprehensive test of both returns and dividend growth predictability should be performed simultaneously. To my best knowledge, there is limited study based on dividend growth predictability or study that employs both predictive regressions at the same time.

Despite positive evidence regarding long-horizon returns predictability, recent works seem to gain increasing creditability on criticizing the statistical and econometric methodologies used in those literatures. Overall, there are a number of reasons why the empirical results of long-horizon returns predictability should be interpreted with caution.

1.7 Problems with Long-Horizon Inferences

There are several difficulties with long-horizon returns that stem from the characteristics of the long-time span of data. Typically, the traditional statistical inferences are invalid since the asymptotic approximations break down. This section
briefly discusses the main potential problems faced by researchers and also provides the remedial treatment to mitigate those problems.

1.7.1 Overlapping Returns

Relating to the characteristics of long-horizon study, the problem of small sample size is under consideration (small sample bias). To be specific, once using non-overlapping data, the researchers will end up with the problem of large estimation errors due to the small sample size. Such large estimation errors lead to several difficulties when making inferences from long-horizon regression. The common approach is to work with overlapping data, which complicates inferences based on Ordinary Least Squares (OLS) regression results. Hansen and Hodrick (1980) address the problem by using regression with k-overlapping returns and show that residuals are autocorrelated up to order (k-1) even under the null hypothesis of no predictability, which makes an assumption of homoscedasticity inappropriate. As is well known, OLS standard errors are biased in the presence of autocorrelated and heteroscedastic residuals. This means that all standard errors need to be corrected by using the robust standard errors based on Newey and West’s (1987) method.

1.7.2 Spurious Regression

A spurious regression has been well documented since Granger and Newbold (1974), and most commonly occurs when the regressor is nonstationary. In addition, Ferson, Sarkissian, and Simin (2003) show that spurious regressions may arise when the regressor is a highly persistent series. Specifically, the spurious regression which has a high R^2 and when the t-statistics tend to be significant has no economic meaning. Incorporating nonstationary or unit root variables in estimating the regression equations using the OLS method yields misleading inferences. Therefore, the nonstationary variable must be either transformed to be stationary or tested by an appropriate approach (i.e., cointegration test). Nevertheless, Perron (1989) has suggested that the observed "unit-root" behavior may have been the result of failure to account for a structural change in the data. This implies that the power of unit root test is low in terms of discriminating between nonstationary series and stationary series with a structural break or a highly persistent stationary series.
1.7.3 Structural Break and Parameter Instability

A test for predictability using a long series of return could be affected by changing behavior in predictive variables over time. The presence of structural change in data can influence the statistical inference of test statistics, which has been documented by Bai (1994). However, the structural stability of predictive regression models of stock returns has received limited attention in the extant literature. Instead of formal tests, structural change is typically addressed by estimating predictive regression models for various subsamples. The formal multiple unknown structural breaks test proposed by Bai and Perron (1998) should be applied to investigate the possible structural break if any to locate the accurate break date in the data.

1.7.4 Endogeneity Problem

An endogeneity problem could also arrive as the result of the overlapping data (Stambaugh, 1986). To account for this, the system of equation approach should be considered. Campbell, Lo, and MacKinlay (1997) address the advantage of using the Vector Autoregression (VAR) approach because it treats all variables as endogenous variables and then estimates several processes simultaneously. However, the predictive performance of the VAR model is based on how to define the structure of VAR system. Hodrick (1992) shows that once the structure of the VAR system is correctly specified, the corresponding result of the VAR is better than that of long-horizon regressions.

The other advantage of using the VAR system is the ability to trace the movement of the variable in the presence of shock through the impulse-response function. In addition, the interpretation of interrelationships among the variables in the VAR system can be done by using (forecast error) variance decomposition, which represents the proportion of fluctuation in each series due to its own innovation and innovations in other series in the system.

1.8 Dissertation Outline

This dissertation is outlined as follows:

Chapter 1 contains an introduction to long-horizon predictive regression. This chapter briefly reviews related literature and provides a theoretical background based on the present value model of stock prices.
Chapter 2 provides insight into the cointegration relationship between log of prices and log of dividends. A long-run relationship between those two variables is expected according to the present value framework. The cointegration methodology is applied to test such a long-run relationship. This is the first step in evaluating the property of the log dividend-price ratio as a predictor of predictive regression. Specifically, if the log of prices and log of dividends are cointegrated, the linear combination, which is a log dividend-price ratio, must be stationary. Hence, the log dividend-price ratio is a proper predictor of predictive regression since it does not violate the classical assumption of linear regression.

Next, Chapter 3 explores the evidence from previous chapter which indicates that there is a structural change in the cointegration relationship between log of prices and log of dividends. Thus, Chapter 3 is focused on instability issues. In this chapter, the possible structural changes in the mean of the log dividend-price ratio are further investigated. Then, the proper methods are drawn in order to take account of the information of the structural break. Lastly, predictive power using the log adjusted dividend-price ratio is compared to that using the log dividend-price ratio.

Chapter 4 investigates the permanent and temporary components of stock prices using the Vector Autoregression (VAR) framework. Specifically, the VAR system is able to trace the responses to a dividend shock and an expected return shock. In addition, the impulse-response analysis reveals that a price rise with no change in dividends results in lower subsequent returns, while a price rise that comes with a dividend rise does not result in lower subsequent returns. This is another piece of evidence that indicates that dividend is unpredictable and price shows a long and obviously reversion back to the mean. In other words, price shocks are temporary or price responds to its own shock temporarily and hence it reverts to its original level. In contrast, dividend shocks are permanent, so price responds to dividend shock permanently and hence such an effect does not die out. A dividend does not respond to price shock but only responds to its own shock.

Finally, Chapter 5 concludes and provides a discussion related to possible implementations.
CHAPTER 2

THE COINTEGRATING RELATIONSHIP BETWEEN STOCK PRICES AND DIVIDENDS

2.1 Introduction

According to the present value model, stock prices are determined by the present value of expected future dividends with discount rate (see Campbell, Lo, and MacKinlay, 1997; Cochrane, 2005). Using the log-linear approximation, Campbell and Shiller (1988) showed that stock price movement is one-by-one proportional to change in dividend. This implies that the dividend-price ratio will be constant in the long-term. Moreover, deviations in the realized dividend-price ratio from a constant level might then result in either changes in the price or changes in the dividend or both. Under the cointegration framework, this present value model shows that the log of stock price and the log of dividend are cointegrated with \((1, -1)'\) cointegrating vector and movement of either price or dividend or both can be explained by the error-correction process of deviation in the dividend-price ratio series. Therefore, either stock returns or dividend growth (or both) can be predicted using the dividend-price ratio as a predictive variable.

However, the literature related to the cointegration between stock prices and dividends is so voluminous, one cannot draw general conclusions. To be more specific, some papers find evidence for cointegration between stock prices and dividends (see e.g., Campbell and Shiller, 1987), while some papers show no cointegration between such variables (see e.g., Komai Jiranyakul, 2008). Further, the realized dividend-price ratio is highly persistent and there is weak evidence of no unit root (see e.g., Lattua and Nieuwerburgh, 2008).

In the presence of non-stationary variables, Granger and Newbold (1974) showed a possible problem of spurious regression, which has a high \(R^2\) and t-statistics
tend to be significant. However, such results have no economic meaning. Incorporating nonstationary or unit root variables in estimating the regression equations using OLS method yields misleading inferences. Perron (1989) has suggested that the observed "unit-root" behavior may have been the result of failure to account for a structural change in the data. In conclusion, there is a twofold explanation relating to the existence of no cointegration. One is that prices and dividend do not have a long-run relationship. Another one is that there is a structural change in long-run relationship and hence the cointegration relationship among variables vanishes.

In this chapter, to address the stability of the relationship in the dividend-price ratio and its implication for stock return predictability, several tests are then performed in order to check whether the log dividend-price ratio is determined by a linearly-stable cointegration relation between the log of stock prices and log of dividend. The rest of this chapter is organized as follows. The related literature is reviewed in section 2.2. Section 2.3 provides a linkage between econometric methodologies with the present value model of stock returns. The empirical findings on the Stock Exchange of Thailand are presented in Section 2.4, and Section 2.5 concludes.

2.2 Literature Review

The cointegration concept has led to thousands of empirical studies that 1) seek to find a long-run relationship among variables and also 2) use the Error Correction Model (ECM) to demonstrate predictability for some cointegrated variables. For example, in the economic area, it was applied to money demand studies (see e.g., Johansen and Juselius, 1990), purchasing power parity (PPP) theory studies (see e.g., Taylor, 1988 and Kim, 1990), the permanent income theory of consumption studies (see e.g., Campbell, 1987), and in testing the relationship between macro variables such as inflation, interest rates, and consumption-wealth ratios. The applications in finance are, for example, the studies of the long-run relationship between futures or forward prices and spot prices (see e.g., Hakkio and Rush, 1989; Brenner and Kroner, 1995; Ackert and Racine, 1999), the studies of the expectation theory of term structures (see e.g., Campbell and Shiller, 1987), and the studies of the
present value relationship between stock prices and dividends (see e.g., Campbell and Shiller, 1987, 1988; Lee, 1996; Power and Marsh, 1999; Komain Jiranyakul, 2008).

Obviously dividends and prices both meander in ways that seem unrelated but that theoretically prove over the long run to be cointegrated. Although the present value model of stock price is simple in its structure, there will be an econometric problem if the least squares method is used to estimate such a relationship. To be more specific, the statistical inferences are not valid under the nonstationarity case. Consequently, empirical analyses of the validity of present value models have been extensively conducted in the cointegration framework.

A pioneer work of Campbell and Shiller (1987) applied the Engle-Granger cointegration, which enabled them to deal effectively with the nonstationarity problem of data; prices and dividends in particular. They used annual prices and dividends on Standard and Poor’s composite stock price index from 1871 to 1986. Unfortunately, the power of their test of the present value model for stocks was “low.” However, they remarked that their failure to uncover a long-run relationship between stock prices and dividends may have been the fault of their test rather than the absence of such a relationship in practice. Similar results were also found by Diba and Grossman (1988).

Rather than using level of dividend and price, Froot and Obstfeld (1991) applied the present value relationship to the time-varying discount rate, which was introduced by Campbell and Shiller (1988), by exploring the relationship between the log of prices and the log of dividend. Using U.S. data from 1900 to 1988, they found mixed evidence of cointegration, depending on the specification of the deterministic component in the unit root test of the residual.

Power and Marsh (1999) worked from a database of 56 large U.K. companies and found empirical support for the theoretical relationship between expected dividends and prices. Chang, Chen, Su, and Chang (2008) employed the newly-developed panel unit root test and cointegration technique to determine the long-run relation between stock prices and earning per shares in Taiwan’s stock market from June 1991 to February 2005 and reported that there exists a significant cointegration relationship between stock prices and dividends.
Despite many papers finding evidence to support cointegration, many cases of no or very little evidence in favor of cointegration were found. For example, using a variety of time series, which ended in the late 1980s, Craine (1993) was unable to reject the null hypothesis that the log price-dividend ratios contain a unit root. Lamont (1998) also provided evidence in favor of a unit root in the log dividend–price ratio, relying on U.S. quarterly data 1947:1-1994:4 and standard Dickey-Fuller tests. Similarly, Balke and Wohar (2002) were also unable to reject the null hypothesis of a unit root by applying Dickey-Fuller tests for the log price-dividend ratio for U.S. quarterly data 1953:2–1999:1. The no cointegration relationship was also found using non-U.S. data. Komain Jiranyakul (2008) examined the present value model using the Stock Exchange of Thailand (SET) index and aggregated market dividends from 1975:4 to 2007:12, both monthly and annually, and found no cointegration between stock prices and dividends from either the Engle-Granger cointegration test or the bounds testing for cointegration.

Does the evidence that prices and dividends often appear to be not cointegrated imply that the present value model for stock prices is incorrect? In other words, what is a possible explanation of the unit root process in the log dividend-price ratio series? Perron (1989) suggested that the observed "unit-root" behavior may have been the result of a failure to account for a structural change in the data. Hence, rejection of cointegration does not necessarily imply no long-run relationship between price and dividend. Instead, if there is a structural change, the test is biased toward accepting the null hypothesis of a unit root, even though the series is stationary within each sub-period. In sum, the cointegrated relationship among variables vanishes or is changes over time because of structural change. Novel methods, such as those of 1) Gregory and Hansen (1996), which allow for a shift in the intercept or in the slope and intercept of the long-run relationship, or 2) the residual-based test of cointegration over subsamples of data (e.g. Davidson and Monticini, 2010), are then applied.

Likewise, in the stock return predictability studies alone, there are many papers that examine the predictability of stock return using cointegrated variables such as the dividend-price ratio or dividend-earnings ratio (see e.g., Campbell and Shiller, 1987, 1988; Fama and French, 1988; Hodrick, 1992; Kothari and Shanken,
1997; Cochrane, 2005) and cay\(^1\) (see Lattua and Ludvigson, 2001). The predictability of stock return, especially over the long-horizon using above variables, is called “stylized fact” (Cochrane, 1999). The widely-cited studies of Cochrane (2005, 2008) provide favorable evidence to support stock return predictability using the dividend-price ratio in U.S. data. He used the present-value relationship to jointly study return and dividend growth predictability. He wisely argued that the lack of dividend growth predictability gives stronger evidence than the presence of return predictability. Lewellen (2004) improved the test of return predictability by using knowledge of the price-dividend ratio’s autocorrelation. Similarly, Pastor and Stambaugh (2009), who used the Bayesian approach to incorporate prior knowledge about the correlation between the unexpected return and innovation in the expected return, together with the Kalman filter, reported that their return predictive systems using the dividend-price ratio yielded higher estimated precision. Recently, work by Van Binsbergen and Koijen (2010) has shown that a latent-variables approach within a present-value framework can also be successfully used to estimate both future returns and dividend growth.

Although the dividend-price ratio should be used to predict both stock returns and dividend growth, most studies focus on return predictability. The general conclusion of the extant literature is that in the post Second World War period the dividend-price ratio was able to predict aggregate returns, but not dividend growth (see e.g., Cochrane, 1992, 2005; Lettua and Ludvigson, 2005). Even though there is positive evidence of stock returns predictability, there is growing evidence supporting dividend growth predictability, especially when using U.S. data before the Second World War (Chen, 2009) or testing non-U.S. data (see e.g., Engsted and Pedersen, 2010 and Rangvid et al., 2011). Chen (2009) challenged the “stylized fact” by showing that for the period up to the end of the Second World War, the opposite predictability pattern characterized the U.S. stock market. Dividend growth was strongly predictable from 1872 to 1945 but it completely disappeared during the Second World War in particular. Yun (2011) examined the NYSE, AMEX, and

\(^1\) Variable \((cay)\) is based on a cointegrating relationship between consumption, aggregate labor income, and aggregate financial wealth.
NASDAQ stocks for the period of 1945 to 2010 and documented that the dividend-price ratio is able to predict both returns and dividend growth rates at a statistically-significant level with higher R-squared values. Three European countries (Denmark, Sweden and the UK) were used in the study of Engsted and Pedersen (2010), and surprisingly they found that the predictability patterns in European stock markets are in many ways quite different from that which characterize the U.S. stock market. In particular, the dividend growth rather than returns was strongly predictable by the dividend-price ratio in Sweden and Denmark. The evidence from the U.K. was mixed but it was still quite similar to that from the U.S. Recently, Rangvid et al. (2011) investigated dividend growth predictability around the world, in 50 countries including Thailand, and found that dividend growth predictability is stronger in medium-sized and smaller countries. In addition, dividend growth predictability was weaker in developed countries where the typical firms are large and the quality of institutions is high. Their results indicated that dividend growth predictability is country-specific in the sense of local firm characteristics, dividend smoothing policy, and institutional quality.

2.3 Cointegration, Error Correction, and Predictive Regression in the Present Value Model of Stock Prices

In this section, the theory of cointegration and how it relates to the error correction model and predictive regression are summarized. Furthermore, they are linked to the present value model of stock prices testing.

Despite the existence of individually nonstationary characteristics, a linear combination of two or more time series can be stationary and cointegrated. Following Granger's (1981) conceptions of cointegration, Engle and Granger (1987) extended the relationship between cointegration and error correction models to develop estimation and test procedures. Specifically, they proved that cointegration and the error correction model (ECM) are the same thing on two sides of the coin, i.e. cointegration entails a negative feedback involving the lagged levels of the variables, and a lagged feedback entails cointegration.
DEFINITION (Engle and Granger, 1987): A vector \( x_t \) is said to be cointegrated of order \((d, b)\), denoted \( x_t \sim CI(d, b) \), if (1) all components of \( x_t \) are integrated of order \( d \) (stationary in \( d\)th differences) and (2) there exists at least one vector \( \beta \) such that the linear combination, \( \beta'x_t \), is integrated of order \((d - b)\), where \( b > 0 \).

According to the definition, cointegration typically refers to a linear combination of nonstationary variables. From the present value model, which states that for two variables, \( h_t \) and \( H_t \), \( H_t \) is a linear function of the present discounted value of expected future \( h_t \):

\[
H_t = \theta (1 - \delta) \sum_{i=0}^{\infty} \delta^i E_h_{t+i} + c_t
\]

where \( \theta \) is the coefficient of proportionality and \( \delta \) is the discount factor. Furthermore, the present value model of stock prices indicates that the stock prices \( (P_t) \) are determined by the present value of expected future dividends \( (D_t) \) and discount rate. Campbell and Shiller (1988), using a log-linear approximation, show that in the long-run, the log of stock price \( (p_t = \ln P_t) \) is proportional to log of dividends \( (d_t = \ln D_t) \) one-by-one. In other words, this also implies that the log of stock price and the log of dividend are cointegrated with the cointegrating vector \((1, -1)'\) and that the log dividend-price ratio is constant and has a stationary property. Let \( Y_t = (p_t, d_t)' \), an econometric specification for such a relationship can be expressed as

\[
p_t = \alpha + \beta_2 d_t + e_t
\]

or

\[
\log p_t - \log \beta_2 d_t = e_t
\]

The constant \( \alpha \) is restricted to be zero following Campbell and Shiller (1987, 1988). Once normalizing the cointegrating vector on \( p_t \) so that \( \beta = (1, -\beta_2)' \), it is proved to be equal \((1, -1)'\) by Campbell and Shiller (1988).

Since the error term \( (e_t) \) must be stationary, it follows that the linear combination of dividends and prices \( (p_t - \beta_2 d_t) \) must also be stationary. This is a basic concept of the residual-based test of Engle and Granger (1987). The cointegrating coefficient \( \beta_2 \) is estimated by the least squares method from equation (2.2) and the estimated regression can be written as

\[
\hat{p}_t = \hat{\alpha} + \hat{\beta}_2 d_t
\]
The cointegrating residual ($\hat{r}_t$) can be implied from equation (2.2) and (2.4), and is supposed to be stationary process,

$$\hat{r}_t = p_t - \alpha + \hat{\beta}_2 d_t.$$  \hspace{1cm} (2.5)

Moreover, if $\alpha$ and $\hat{\beta}_2$ are zero and one, respectively, as suggested by Campbell and Shiller (1988), equation (2.4) implies that $\hat{r}_t = d_t$ and hence the cointegrating residual ($\hat{r}_t$) is also equal to

$$\hat{r}_t = p_t - d_t.$$  \hspace{1cm} (2.6)

Under the Granger representation theorem, the existence of cointegration relationship implies that their time paths are influenced by the deviations from a long-run equilibrium. If the system is trying to return to such an equilibrium, at least some of the cointegrated variables must respond to the magnitude of disequilibrium. To be more specific, if the realized dividend-price ratio is greater than the long-run equilibrium level, as indicated by the cointegrating vector, the future dividends will tend to decrease or the future prices will tend to increase in order to bring the dividend-price ratio back to the long-run equilibrium level. Similarly, if the realized dividend-price ratio is lower than the long-run equilibrium level, the future dividends will tend to increase or future prices will tend to decrease in order to return the dividend-price ratio back to the long-run equilibrium level. The dynamic model implied by this discussion is called the Error Correction Model (ECM), which can be expressed as follows:

$$\Delta p_t = \gamma (d_{t-1} - p_{t-1}) + e_{p,t}$$  \hspace{1cm} (2.7)

$$\Delta d_t = \phi (d_{t-1} - p_{t-1}) + e_{d,t}$$  \hspace{1cm} (2.8)

where $(d_t - p_t) = \ln \left( \frac{d_t}{p_t} \right)$ denotes the logarithm of the dividend-price ratio.

Likewise, the predictive regression is based on the concept of ECM if information is updated to the present. The typical stock returns and dividend growth predictive regressions used in literatures are written as

$$\Delta p_{t+k} = \gamma_f (d_t - p_t) + e_{p,t+k}$$  \hspace{1cm} (2.9)

$$\Delta d_{t+k} = \phi_f (d_t - p_t) + e_{d,t+k}$$  \hspace{1cm} (2.10)
where \( \Delta p_{t+k} = r_{t+k} \) denotes stock returns over \( t + k \) horizons, and \( \Delta d_{t+k} \) represents dividend growth over \( t + k \) horizons, where \( k = 1, 2, \ldots, K \) (i.e. Cochrane, 2005: 392 Table 20.1). According to equation (2.9) and (2.10), the \( t + k \) -horizon future returns (dividend-growth) are regressed onto a one period predictor; in other words, the \( t + k \) -horizon future returns (dividend-growth) is predicted by the current log dividend-price ratio.

### 2.4 Empirical Evidence

#### 2.4.1 Data

The data comprise aggregate monthly closing stock prices (\( P \)) and the aggregate monthly dividend-price ratio (\( DP \)) on the Stock Exchange of Thailand index (SET index). The data were obtained from the Stock Exchange of Thailand and cover the period from the beginning of the stock market, 30 April 1975, to 31 August 2011. All data were transformed into logarithm form (denotes in small letter).

Specifically, the log of price \( p_t \) was calculated from \( \ln(p_t) \), and similarly, the log dividend-price ratio was simply calculated from \( \ln(DP_t) \). For the log returns \( r_t \), it was calculated from \( \ln \left( \frac{p_t}{p_{t-1}} \right) \). The reason for using log returns rather than the simple or raw return was twofold. First is that the log returns is normally distributed since prices are typically assumed to be log normal (cannot be a negative value). And the second one is the time additive property, which makes the calculation of compound returns easier. The linkage between log returns and simple return \( R_t \) can be shown as follows:

\[
R_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{P_t}{P_{t-1}} - 1.
\]

Therefore, the logarithm of 1 + \( R_t \) is equal to log return \( r_t \):

\[
\ln(1 + R_t) = \ln \left( \frac{P_t}{P_{t-1}} \right) = r_t.
\]

---

2 The dividend yield or the dividend-price ratio is the total dividend payments divided by the market capitalization. Since 30 June 2004, the Stock Exchange of Thailand has changed the definition of total dividend payments from 12-month total dividend payments to total annual dividend payments based on fiscal year. Moreover, the market dividend-price ratio is calculated from all listed stocks even the ones do not pay dividend on that year.
If the returns are very small (common for very short period i.e. daily), the log returns and the simple returns should approximately equal. Next, considering the holding period of $n$, the compound returns over $n$ holding periods using a simple return is calculated as a product of gross simple returns:

$$\prod_{i=2}^{n} (1 + R_i) = (1 + R_2) \cdot (1 + R_3) \cdot \ldots \cdot (1 + R_n).$$

Unfortunately, according to the probability theory, the product of normally-distributed variables is not normal. Instead, the sum of these variables is normal such that the compound returns over $n$ periods are:

$$\sum_{i=1}^{n} \ln (1 + R_i) = \ln(1 + R_1) + \ln(1 + R_2) + \cdots + \ln(1 + R_n).$$

$$\sum_{i=1}^{n} \ln \left( \frac{P_i}{P_{i-1}} \right) = \ln \left( \frac{P_2}{P_1} \right) + \ln \left( \frac{P_3}{P_2} \right) + \cdots + \ln \left( \frac{P_n}{P_{n-1}} \right).$$

$$\sum_{i=1}^{n} \ln (1 + R_i) = \ln(P_2) - \ln(P_1) + \ln(P_3) - \ln(P_2) + \cdots + \ln(P_n) - \ln(P_{n-1}).$$

$$\sum_{i=1}^{n} \ln \left( \frac{P_i}{P_{i-1}} \right) = \ln \left( \frac{P_n}{P_1} \right).$$

Thus, the compound return over $n$ periods is simply the difference between the log of ending price and the log of initial price. This is very impressive and the compounding of the log returns is normally distributed.

The dividend was computed as suggested by Lewellen (2004) as follows:

$$D_t = DP_t - P_t,$$

and then the natural logarithm was taken to obtain the log of dividend, $d_t$. Moreover, dividend growth, $\Delta D_t$, and log dividend growth, $\Delta d_t$, were computed in the same way as returns.

### 2.4.2 Descriptive Statistics

Table 2.1 provides the descriptive statistics for the variables used in this dissertation. The log returns has a mean of 0.005, while the simple returns has a mean of 0.009. The difference results from the large trading period, monthly in particular.
The mean of the dividend-price ratio is 0.045, which is 9 times larger than that of the log returns. However, both log returns and simple returns are more volatile than the dividend-price ratio. In addition, the log returns exhibits a negative skew whereas the dividend-price ratio has a positive skew.

When looking at the autocorrelation, as is well known, the dividend-price ratio is very persistent. The first- and second-order autocorrelations are 0.984 and 0.783, respectively. The log returns is less persistent with the first- and second-order autocorrelations of 0.109 and 0.054, respectively. Moreover, the log returns shows a negative autocorrelation in the longer horizon.

**Table 2.1** Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>$\rho_1$</th>
<th>$\rho_{12}$</th>
<th>$\rho_{24}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log of stock index (p)</td>
<td>5.909</td>
<td>0.837</td>
<td>-0.229</td>
<td>0.990</td>
<td>0.858</td>
<td>0.708</td>
</tr>
<tr>
<td>Log of dividend (d)</td>
<td>2.645</td>
<td>0.611</td>
<td>-0.380</td>
<td>0.991</td>
<td>0.807</td>
<td>0.501</td>
</tr>
<tr>
<td>Log Returns (r)</td>
<td>0.005</td>
<td>0.085</td>
<td>-0.403</td>
<td>0.109</td>
<td>0.054</td>
<td>-0.069</td>
</tr>
<tr>
<td>Simple Returns (R)</td>
<td>0.009</td>
<td>0.084</td>
<td>0.169</td>
<td>0.106</td>
<td>-0.049</td>
<td>-0.074</td>
</tr>
<tr>
<td>Dividend-price ratio (DP)</td>
<td>0.045</td>
<td>0.025</td>
<td>0.680</td>
<td>0.984</td>
<td>0.783</td>
<td>0.602</td>
</tr>
<tr>
<td>Log Dividend-price ratio (dp)</td>
<td>-3.264</td>
<td>0.598</td>
<td>-0.321</td>
<td>0.983</td>
<td>0.748</td>
<td>0.527</td>
</tr>
</tbody>
</table>

**Note:** Sample Period: Apr 1975 - Dec 2010, 429 Monthly Observations

### 2.4.3 Testing for Unit Roots

Theory suggests the existence of a long-run relationship between stock prices and dividends. If these variables are stationary in their first difference, I(1) series in particular, the cointegration technique can be used to model the long-run relationships among these variables. Hence, pre-testing for unit roots is often a first step in cointegration modeling.
As can be seen from Figure 2.1, the log of stock price and the log of dividend processes seem to move together and look like I(1) with a drift. To formally test for the presence of a unit root in both series, the Augmented Dicker Fuller (ADF) and the Phillips-Perron (PP) tests were performed. The ADF, developed by Said and Dickey (1984), tests the null hypothesis that time series $y_t$ is I(1) against the alternative that it is I(0), assuming that the data have an ARMA structure. Table 2.2 reported that under the ADF test, the test statistic for log of stock prices was -1.546, whereas the critical values under 1%, 5%, and 10% were -3.445, -2.868, and -2.570, respectively. A similar result was obtained for the log of dividend series. The test statistic was -2.690 when the critical values under 1%, 5% and 10% were -3.446, -2.868 and -2.570, respectively. Therefore, the null hypothesis of the unit root process failed to reject either the log of stock prices or the log of dividends. Incidentally, when performing the ADF test in the first difference series, returns and dividend growth in particular, the test statistics were statistically significant at a conventional level. Hence, stock returns and dividend growth do not contain a unit root process.

The PP unit root test, introduced by Phillips and Perron (1988), differs from the ADF test in how to deal with serial correlation and heteroscedasticity in the errors. The PP test showed the same results as the test statistics of -1.265 and -1.469 for the log of prices and log of dividends, respectively. Again, the null hypothesis of the unit root process was failed to reject. However, the PP test for returns and dividend growth showed that the null hypothesis of a unit root was rejected with the test statistics of -18.516 and -16.729, respectively. In sum, both ADF and PP tests confirmed the same results.
A shortcoming of the ADF test is its relative low power to discriminate between the near unit root process and the actual unit root process (Elliott et al., 1996). To overcome this issue, a direct test of the null hypothesis of stationary process against the alternative of nonstationary process; the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test, was performed. The KPSS test statistics were 1.547 and 0.554 for log of prices and log of dividend respectively, and were statistically significant at a conventional level. In other words, the null hypothesis of stationary was rejected, which implies that both series are nonstationary processes. However, the null hypothesis of stationary was failed to reject with the test statistics of 0.092 and 0.086 for returns and dividend growth. Overall, the unit root tests and KPSS test confirmed the existence of a unit root in level series, while the first difference series did not contain a unit root. Likewise, the log of prices and log of dividend were nonstationary series while returns and dividend growth were stationary series.
### Table 2.2 Unit Root Tests Analysis Using Level Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF test</th>
<th>PP test</th>
<th>KPSS test</th>
<th>ZA test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log of stock price (p)</td>
<td>-1.546</td>
<td>-1.265</td>
<td>1.547***</td>
<td>-</td>
</tr>
<tr>
<td>Log of dividend (d)</td>
<td>-2.690</td>
<td>-1.469</td>
<td>0.554**</td>
<td>-</td>
</tr>
<tr>
<td>Log Returns (r)</td>
<td>-12.476***</td>
<td>-18.516***</td>
<td>0.092</td>
<td>-</td>
</tr>
<tr>
<td>Log Dividend growth (Δd)</td>
<td>-16.415***</td>
<td>-16.729***</td>
<td>0.086</td>
<td>-</td>
</tr>
<tr>
<td>Log Dividend-price ratio (dp)</td>
<td>-2.402</td>
<td>-2.227</td>
<td>1.234***</td>
<td>-5.097**</td>
</tr>
</tbody>
</table>

**Note:** *, **, *** denotes 10%, 5%, and 1% significant level, respectively.

Interestingly, the log dividend-price ratio series, which is very persistent, contains a unit root. The ADF test statistic with intercept was -2.402, whereas the critical value at the 10% level was -2.570. A similar result was found with the PP test with the test statistic of -2.227, which is also greater than -2.570, the critical value under 10%. In addition, the null hypothesis of stationary was rejected with the KPSS test statistic of 1.234, which was less than the critical value at 10%, 0.347. Nevertheless, the results are consistent with those of Lettua and Nieuwerburgh (2008), who found that the log of dividend-price ratio was nonstationary. The high persistent series is a well-known characteristic of the dividend-price ratio in empirical study; however, the evidence of the unit root is mixed. Perron (1989) suggested that the observed "unit-root" behavior may have been the result of failure to account for a structural change in the data. Specifically, in performing unit root tests, care must be taken if it is suspected that structural change has occurred such that the ADF test is biased toward the non-rejection of a unit root. The evidence of structural changes in financial ratios, including dividend-price ratio, were documented by McMillan (2007), Lettua and Nieuwerburgh (2008), and Frömmel and Kruse (2012), for example.³

³ A detailed discussion about model instability and structural break test are provided in Chapter 3.
To overcome the above discussion, Zivot and Andrews's (1992) unit root test with endogenous structural break (ZA test) was performed. The ZA test is a sequential test which utilizes the full sample and uses a different dummy variable for each possible break date. Note that the null hypothesis is a unit root without a structural break. The test statistic of -5.097 rejected the null hypothesis at the 5% significance level. Therefore, the log dividend-price ratio is stationary with the structural break.

2.4.4 Cointegration Tests

The method of estimation of the standard regression model, the Ordinary Least Squares (OLS) method, is based on the assumption that the means and variances of the variables being tested are constant over the time. If the variables are nonstationary, the statistical inference does not hold since the least-squares estimators are not consistent. Hence, the estimation of long-run relationship between those variables should be based on the cointegration method.

Campbell and Shiller (1987, 1988) provided a theoretical framework to explain the long-run relationship between stock price and dividend with the cointegrating vector (1, -1)'. Therefore, two basic cointegration tests, Engle and Granger (1987) and Johansen (1988), were applied to test the existence of such a relationship and to estimate the cointegrating vector between variables.

Firstly, Engle-Granger methodology (1987), which is a residual-based test to determine whether the residual terms are stationary, was performed. Let \( Y_t = (p_t, d_t) \); a econometric specification for such a relationship can be expressed as equation (2.2). The Ordinary Least Squares (OLS) is used to estimate the equation and the results are shown as follows:

\[
\begin{align*}
\hat{\beta}_t &= 3.38 + 0.96d_t \\
(\text{SE}) &= (0.1284) (0.0473)
\end{align*}
\]

where \( R^2 = 0.4895 \)

Figure 2.2 plotted the residual series where drifts in mean are possible for a different period of time. Since the existence of the cointegration relationship is based on the stationarity of residual term (Equation (5)), the ADF test with no intercept was used to perform such a test. The ADF t-statistic was -2.634, while the MacKinnon (1991) critical value was -3.02; therefore the null hypothesis of no cointegration was failed to reject at the 10% significance level. In other words, there was no long-run
relationship (no cointegration) between price and dividend over the sample period because the residual term $\hat{\xi}_1$ was nonstationary. The non-existence of cointegration was not surprising since Komain Jiranyakul (2008) also reported similar findings. Specifically, using both the Engle and Granger cointegration and the bound testing for cointegration, Komain Jiranyakul (2008) also found no cointegration between stock price and dividend in Thailand over the period of 1975 to 2007.

Even though the estimate of $\hat{\xi}_2$ was 0.96 and was very close to one, implied by the present value model of the stock prices, the asymptotic distribution of $\hat{\xi}_2$ was asymptotically biased and was non-normal and inefficient. Consequently, the usual OLS standard errors were not correct and invalidated the statistical inferences.

![Figure 2.2 Plot of Residual Term, $\hat{\xi}_2$](image)

Although the Engle-Granger methodology (1987) is easily implemented, it does have some flaws. Particularly, it relies on a two-step estimator, where the first step is to generate residual terms and the second step is to perform a unit root test based on these generated errors. Thus, any error introduced in step 1 is carried into step 2. Fortunately, Johansen's (1988) likelihood-ratio (LR) based test can examine the presence of cointegrating vectors only in one step. Another shortcoming of the Engle-Granger methodology is the ability to estimate only a single cointegrating relationship. Again, Johansen's (1988) LR test permits more than one cointegrating
relationship. Therefore, the Johansen's (1988) LR test was performed to complement the Engle-Granger residual-based test.

The Johansen (1988) methodology relies heavily on the relationship between the rank of long-run impact matrix and its characteristic roots. Two test statistics—the trace statistic and the maximum Eigenvalue statistic, were considered. Moreover, the Johansen method relies on the maximum likelihood (ML) estimator of the reduced rank model and yields asymptotically-efficient estimates of the cointegrating vectors.

**Table 2.3 Johansen’s Cointegration Test**

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>Test Statistic</th>
<th>95% Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trace</td>
<td>Max. Eigenvalue</td>
</tr>
<tr>
<td>$r = 0$</td>
<td>8.324</td>
<td>6.092</td>
</tr>
<tr>
<td>$r \leq 1$</td>
<td>2.251</td>
<td>2.251</td>
</tr>
</tbody>
</table>

**Note:** $r$ is the number of linearly-independent cointegrating vectors.

Table 2.3 reported the trace and maximum Eigenvalue statistics of Johansen's LR test. Both test statistics were less than the 95% critical values. Again, the null hypothesis of zero rank could not be rejected, which indicated that there was no cointegration between the log of prices and log of dividend.

From the Engle-Granger residual-based test and the Johansen LR test, it was able to conclude that there was no evidence of cointegration. However, the absence of a long-run relationship is possible since Perron (1989) suggested that the observed "unit-root" behavior (in residual terms $z_t$) may be the result of failure to account for a structural change in the data. In this sense, evidence against cointegration may exist because of the structural break(s) in the data. Among others, Gregory and Hansen's (1996) cointegration with structural break test may be useful to further clarifying this issue.
However, before investigating the structural break in the coefficient estimated from the cointegrating vector, the parameter stability using rolling and recursive regression were explored. The methodology details are provided in the next section.

### 2.4.5 Parameter Stability Tests

Rolling regression can be used to access the stability of the coefficient estimate in the cointegrating regression over time. The data are initially split into an estimation sample and then the coefficients of cointegrating vector are estimated. The estimation sample is then rolled ahead in a given increment and the estimation is repeated. To assess parameter constancy in this chapter, let \( n = 8 \) years denote the width of a sub-sample or window and define an increment equal to one month. With the 8-year rolling regression, the estimated coefficients of the cointegrating vector (both intercept and slope) are plotted in Figure 2.3. As can be seen, there is some evidence of instability in both the intercept and slope estimated by the rolling regression.

Another simple way to investigate parameter stability is to compute the recursive estimation of coefficients of the cointegrating vector and cointegrating residual. Unlike rolling regression, which has the same estimating window size, recursive regression begins with a sub-sample (normally the minimum required for estimation) to estimate a regression, and then sequentially adds one observation at a time and reruns the regression until the end of the sample is reached. The parameter estimates at the start of this procedure appeared unstable; however, as the sample size increases the estimates should settle down such that if the cointegrating relationship between the log of stock prices and log of dividend is constant over the entire sample period, the recursive estimates should converge into a certain value or not exceed the \( \pm 2 \) standard errors band. Therefore, if the magnitude of the recursive residual suddenly begins to change, a structural break will possibly occur.
Similar results were shown in Figure 2.4, where the recursive residuals were wandering out of two standard errors. Thus, the recursive regression also indicated the instability of the cointegrating regression. In addition, two statistical tests based on recursive least squares, the CUSUM test and the CUSUM of squares test, were computed and plotted in Figure 2.5.

**Figure 2.3** Plots of Estimated Parameters; Intercept and Slope, from Rolling Regression
As its name implies, the CUSUM test involves the calculation of a cumulative sum of residuals calculated from recursive regressions. Under the null hypothesis of parameter stability, the CUSUM test should be equal to zero and the CUSUM of squares test should start from zero and end at one. In practice both are normally plotted with 95% confidence bands and the null hypothesis is rejected when the plot departs from this band.
As can be seen from Figure 2.5, both the CUSUM and CUSUM of squares tests strayed out of a 95% confidence band. Hence, the null hypothesis of parameter stability was rejected. Having found the parameter instability in the cointegrating regression, the cointegration test with structural break is obviously being an alternative method.

### 2.4.6 Cointegration Test with Structural Break

Gregory and Hansen (1996) extended Engle and Granger’s (1987) residual-based cointegration test to test the null hypothesis of no cointegration against the alternative hypothesis of cointegration, which allows for the possibility of a regime shift in the cointegrating vector at an unknown time. Since the Engle-Granger test assumes a time-invariant cointegrating vector, the residual-based test for cointegration proposed by Gregory and Hansen was more appropriate for this data set. As the non-existence of cointegration was found by using the Engle-Granger test, the existence of a time invariant cointegrating relationship could have been the cause of the rejection of no cointegration.

Gregory and Hansen (1996) introduced a residual-based cointegration test which allows for a structural break in either the intercept or the intercept and the cointegrating coefficient at an unknown time. However, the aim of this chapter is to investigate the possible shift in the intercept, so the following cointegrating regression was estimated:
where the dummy variable $D_t$ denotes a structural break and is defined as:

$$D_t = \begin{cases} 1 & \text{if } t > \tau, \\ 0 & \text{otherwise} \end{cases}$$

where $\tau$ denotes the unknown location of the break date. For each $\tau$, equation (2.11) was estimated by OLS yielding the residual $\bar{u}_t$. The ADF test was then performed for each $\bar{u}_t$. This is the standard procedure for the conventional cointegration test; however, Gregory and Hansen's test chooses the smallest ADF test statistic across all values of $\tau$. The reason for selecting the smallest value of the test statistics was that demonstrated evidence against the null hypothesis.

Following the procedure described in Gregory and Hansen (1996), equation (2.11) is estimated with a break at April 1988 ($\tau = 0.37$) and can be expressed as follows:

$$\bar{u}_t = 0.53d_t$$

Again, the existence of cointegrating relationship is based on the unit root test in the cointegrating residual term, $\bar{u}_t$. Since the ADF t-statistic was -4.881, which is greater (in absolute value) than the 5% critical value from Gregory and Hansen (1996: Table 1) (-4.61), the null hypothesis of no cointegration was then rejected at the 5% significance level. Alternatively, once allowing for a possible structural break (shift in mean), there exists a cointegrating relationship between the log of prices and log of dividend.

### 2.4.7 Stock Returns Predictability Using a Cointegrated Variable

Campbell and Shiller (1988) showed that the log dividend-price ratio will be an appropriate variable to be used in the stock returns predictive regression if the log of stock prices and log of dividend are cointegrated with the cointegrating vector $(1, -1)'$. When the log dividend-price ratio with the cointegrating vector $(1, -1)'$ is used as a predictor, it seems that the nonstationary predictor is used in stock return predictive regression. However, the breakdown of the cointegrating relationship between the log of prices and log of dividend results from the structural break, as confirmed by
Gregory and Hansen’s test and Zivot and Andrew’s test. Thus, the log dividend-price ratio is indeed a stationary process but is highly persistent and faces a structural break.

In this chapter, the log dividend-price ratio series without any adjustment for structural break was used as a predictor. The long-horizon stock returns regression and dividend growth regression were tested to investigate the ability of the log dividend-price ratio, as suggested by present value theory. However, the issue of model instability will be formally tested in Chapter 3. In addition, the proper adjustment will be considered and the long-horizon predictive regressions will be revisited.

In particular, equation (2.9) and (2.10) were estimated for the whole sample period using the log of dividend-price ratio as a predictor. The future returns horizons and dividend growth horizons range from 1 to 5 years, similar to those reported in Cochrane (2005). In the long horizon returns predictive regression (equation (2.9), the expected sign is positive and should increase with the forecasting horizon \( k \). Specifically, if current price is too low (current dividend-price ratio is too high, ceteris paribus), it will move up (in order to adjust to long-run equilibrium) in the future period and then lowers the future dividend-price ratio as well as introduces positive returns. As a result, a high current dividend-price ratio predicts a higher future price or positive returns. On the other hand, a negative sign is expected for the long-run dividend growth predictive regression (equation (2.10). When the current dividend is too low (current dividend-price ratio is too low, similarly), it will tend to go up (in order to adjust to long-run equilibrium) in the future period and hence yielding a higher future dividend-price ratio. Therefore, a low current divided-price ratio predicts higher future dividend growth.
Table 2.4  Estimation Results for the Predictive Regression Models

<table>
<thead>
<tr>
<th>Horizon k (years)</th>
<th>$\Delta d_{t+n} = \gamma_d (d_t - P_t) + \sigma_d$</th>
<th>$\Delta r_{t+h} = \phi_r (d_t - P_t) + \sigma_r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_d$</td>
<td>$\sigma_d$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1</td>
<td>0.095</td>
<td>0.052</td>
</tr>
<tr>
<td>2</td>
<td>0.240</td>
<td>0.076</td>
</tr>
<tr>
<td>3</td>
<td>0.309</td>
<td>0.102</td>
</tr>
<tr>
<td>4</td>
<td>0.334</td>
<td>0.134</td>
</tr>
<tr>
<td>5</td>
<td>0.383</td>
<td>0.153</td>
</tr>
</tbody>
</table>

Source: Newey and West, 1987: Standard Errors are Computed, Method to Control for Heteroscedasticity and Serial Correlation.

As discussed in Chapter 1, the longer the horizons, the larger the coefficients result from the high autocorrelation of the log dividend-price ratio - 0.984 in this data set. If daily returns are very slightly predictable by a slow-moving variable, such predictability should add up over long horizons. Therefore, the magnitude of coefficient and $R^2$ is expected to increase with the forecasting horizon $k$.

Table 2.4 reported that the estimated coefficients from the returns predictive regression were significantly increasing over the forecasting horizons with a larger corresponding $R^2$ as expected. In particular, the estimated coefficient for the one-year return predictive regression was marginally significant, 0.095; however, the estimated coefficients for two- to five-year horizons were economically significant. Moreover, the magnitude of the two-year horizon was double that of the one-year horizon. Likewise, the R-square also increased as expected. For the dividend growth predictive regression, the sign of the estimated coefficients were negative, as predicted. The estimated coefficients from first two-year horizon were significant and the coefficient
of the two-year regression increased from one-year regression, from 0.156 to 0.228. However, the estimated coefficients from the longer horizons were gradually decreasing and were insignificant. Such findings were consistent with those reported in Cochrane (2005), in which the log dividend-price ratio was able to predict the returns rather than dividend growth over the long horizon. Nonetheless, the R-squares reported in this study were considerably lower than those reported in Cochrane (2005). In particular, he documented that using U.S. data, 60% of the variation in stock returns was forecastable ahead in the 5-year horizon by using the dividend-price ratio.

Incidentally, the results in Table 2.4 were derived from the predictive regressions using a nonstationary predictor, the log dividend-price ratio. As discussed earlier, the problem of spurious regression may occur (Granger and Newbold, 1974). In particular, it is possible that the estimated coefficients in return predictive regressions are statistically significant when there is no true relationship between the log dividend-price ratio and log return. In other words, if the predictor exhibits nonstationary process, it is very likely that the dependent variable will display a similar stochastic trend. Then, the standard consistency property of the OLS estimators breaks down and consequently the usual test statistics based on normal distribution becomes invalid. Thus far, evidence of return predictability in Stock Exchange of Thailand has not been confidently confirmed.

2.5 Conclusion

The present value model of stock returns implies that the log of prices and dividend is cointegrated and hence the cointegrated variable (the log dividend-price ratio, in particular) is the optimal forecaster for either changes in future prices or changes in future dividends. In other words, the log dividend-price ratio may not be an appropriate variable to be used in the returns predictive regression if there is no cointegration between log of prices and log of dividend with the cointegrating vector \((1, -1)\)', as suggested by Campbell and Shiller (1988).

In this chapter, the predictability of stock return using the dividend price ratio was investigated using the monthly data of Stock Exchange of Thailand from April 1975 to December 2010. First, the cointegration tests, Engle-Granger’s (1987) test
and Johansen’s (1988) test, were applied to the data. The null hypothesis of no cointegration failed to reject both cointegration tests. However, Perron (1989) argues that the ability of the ADF test to reject the unit root hypothesis can be affected by a structural break in the long-span dataset. In particular, the residual-based cointegration test may be biased toward finding no cointegration among variables because the unit root test is unable to discriminate between stochastic trends and deterministic trend alternatives, including models that may have break in trends. Hence, the possibility of parameter instability in the cointegration relationship was carefully investigated using several indicators, i.e. the rolling regression and recursive regression.

Second, the cointegration test, which allows for a structural break in the mean at an unknown break date (Gregory and Hansen, 1996) was performed. Interestingly, once the possibility of a structural break (shift in mean) is allowed for, there exists a cointegrating relationship between log of prices and the log of dividend. Both Engle and Granger's (1987) and Gregory and Hansen's (1996) cointegration tests were able to offer stronger evidence than the parameter constancy tests alone. In particular, if the Engle and Granger test fails to reject the null hypothesis of no cointegration but the Gregory and Hansen test does, this could imply that the failed to reject the null hypothesis of no cointegration is due to the low power of the former test caused by the structural break in the cointegrating vector. In addition, the Zivot and Andrews (1992) unit root test with an endogenous structural break also confirmed the stationary property of the log dividend-price ratio when the endogenous break is allowed for.

Finally, the ability of the log dividend-price ratio to predict future returns and dividend growth was explored. The findings are similar to those reported by Cochrane (2005). More specifically, the log dividend-price ratio is able to predict returns rather than dividend growth over the long horizon. However, such findings may not hold because the predictor is a nonstationary variable. So, the evidence of return predictability in the Stock Exchange of Thailand was not secured due to the possibility of a spurious regression. Enlightened by the evidence of instability in the cointegration relationship as well as the confirmation of the cointegration test with a structural break (Gregory and Hansen, 1996) and the unit root with an endogenous break (Zivot and Andrews, 1992), the formal structural break test (Bai and Perron, 1998) and a proposed solution will be carefully examined in Chapter 3.
CHAPTER 3

INSTABILITY IN RETURNS PREDICTIVE REGRESSION

3.1 Introduction

Early empirical work on stock prices found it very difficult to reject the null hypothesis that stock prices follow a random walk process (Fama, 1970; Meese and Rogoff, 1983). However, following studies provide supporting evidence that stock prices do not follow the random walk process, especially in the long horizon (see e.g., Summers, 1986; Fama and French, 1988; Lo and MacKinlay, 1988; Hodrick, 1992; Lamont, 1998; Cochrane, 1992, 2005, 2008).

Theoretically, in the time-varying expected returns framework, stock returns could be predicted using either their own past information or other predictive variables (Campbell and Shiller, 1988; Cochrane, 1999). During the 1980’s and 1990’s these variables were mostly financial, linking firm fundamentals to future stock returns. However, macroeconomic variables were suggested due to the poor performance of the valuation ratio in the 1990’s.

Even though there is positive evidence of long-horizon returns predictability, several authors have expressed concern that the econometric methodologies used in investigating the series of stock returns in the long span time series could be affected by changing behavior in predictive variables over time. In addition, the assumption of model stability may be invalidated. Specifically, the long-run relationship between prices and their fundamental (e.g. dividend) may be changed (see e.g., McMillan, 2007; and Lettau and Nieuwerburgh, 2008) and evidence of the instability of the return predictive regression has found (see e.g., Pastor and Stambaugh, 2001; Welch and Goyal, 2003; Ang and Bekaert, 2004; Rapach and Wohar, 2005; and Paye and Timmermann, 2006). Therefore, the economic significance of return predictability must be carefully interpreted.
Chapter 2 reported on evidence of the instability in the cointegrating relationship between log of prices and log of dividends in Thailand over the period of 1975:4 – 2010:12. Thus, this chapter further investigated the stability of the predictive variable, the dividend-price ratio in particular, as well as the stability of return predictive regression in more detail. While several studies found evidence of instability in the return predictive regression, they did not perform a formal structural break test in order to determine the exact break date. Hence, to emphasize the structural break issue, the Bai and Perron’s (1998) structural break test was employed and then the dividend-price ratio was adjusted by its subsample mean, as suggested by Lettau and Nieuwerburgh (2008). Moreover, evidence of instability in the cointegrating coefficient from Chapter 2 led to the implementation of a disequilibrium error from the cointegration regression as a predictive variable. And last, the long horizon predictive regressions for both stock returns and dividend growth (similar to equation (2.9) and (2.10) in Chapter 2) were re-estimated using 1) the adjusted dividend-price ratio according to Lettau and Nieuwerburgh (2008) and 2) disequilibrium error from the cointegration regression. The predictive results were then compared with those reported in Chapter 2. Specifically, the predictive power of the log dividend-price ratio and adjusted log dividend-price ratio was evaluated as to whether taking the information about structural break into account improves the predictability or not.

The structure of this chapter is as follows. Section 3.2 summarizes the literatures related to the instability of predictive variables and predictive regression. The econometric methodology used in this chapter is carefully explained in Section 3.3. The empirical results are shown in Section 3.4, and lastly Section 3.5 summarizes the main findings.

3.2 Literature Review

The predictability of stock returns has been well documented in the empirical finance literature. Although there is positive evidence regarding stock returns predictability, there is evidence indicating that the forecasting relationship between returns and financial ratios exhibits significant instability over time. Structural breaks
in the parameters of predictive regressions can occur for a number of reasons, e.g.,
major changes in market sentiment, speculative bubbles, regime changes in monetary
policy, changes in debt management policies, and learning by investors (see Pesaran
and Timmermann, 2002). Moreover, in an international context, breaks may arise as a
result of the market integration process, i.e. the case of European Union and ASEAN.
These possibilities are important because they introduce a new source of risk which
may fundamentally affect the predictability of stock returns. Therefore, ignoring the
stability of return predictive regression may mislead the interpretation and implication
since the estimated coefficients should change over time.

Pastor and Stambaugh (2001) relied on the basic principles of discounting,
which indicate that a shift in the excess returns is likely to be coincident with a price
change in the opposite direction; they included this property in their model using the
Bayesian approach. In addition, the estimation of their model allowed for an unknown
break date (s). Using their framework, the interesting results showed that the excess
returns exhibit an unstable pattern. Particularly, the excess returns rose during the 19th
century and the first few decades of the 20th century, but they declined steadily after
the 1930s. Moreover, the excess returns plunged during the decade of the 1990s.
Likewise, Rapach, Wohar and Wohar (2005) found complementary evidence of
instability in return predictive regression using S&P500 data and noted that there was
a structural break in return predictive regression using the dividend-price ratio around
1990. Using international equity indices with several predictive variables, e.g.
dividend-price ratio, short interest rate, term spread and default risk, Paye and
Timmermann (2006) reported evidence in favor of breaks in the OLS coefficient in
the forecasting of regression of returns. In addition, they showed that breaks do not
occur at the same time across countries.

Unlike the above studies which test the stability of return predictive
regression, some studies have investigated the possibility of a shift in the mean of
predictive variables. For example, McMillan (2007) provides evidence in favor of
structural breaks in financial ratios—the dividend-price ratio and earnings-price ratio
by using data from several countries. Interestingly, he performs Bai and Perron's
(1998) test and finds that the dividend-price ratio exhibits a downward-level shift
while the earnings-price ratio exhibits an upward-level shift over the sample period.
Recently work by Lettua and Nieuwerburgh (2008) has reexamined the stability of the dividend-price ratio in the U.S. and also showed evidence for breaks in the constant mean of the dividend-price ratio. Besides locating the breaks, they assert a simple correcting method for such breaks to improve the predictive power of returns predictive regression.

Furthermore, when performing regression with cointegrated variables, one should bear in mind the possibility of structural change in the cointegration relationship\textsuperscript{1}. The structural breaks in the cointegration relationship mean a significant change in the cointegration parameters or a change in the existence of the cointegration relationship. This implies that the traditional cointegration tests (Engle-Granger's residual based test and Johansen's test) are not adequate if there is a structural break in the cointegration vector. They typically fail to reject the null hypothesis of no cointegration less often than they should and hence lead to a wrong conclusion of no long-run equilibrium relationship. To overcome this problem, the Gregory and Hansen (1996) test should be performed. Evidence of structural changes in the cointegration relationship has been found in many studies. For example, Lee (2004) examines the cointegration relationship between the log of stock prices and log of dividends using U.S. data from 1981 to 2002 and finds evidence in favor of a structural break in the cointegrating vector. In addition, he also finds that the log of stock prices and log of dividends are not cointegrated with the cointegrating vector (1, -1)\textsuperscript{1}. Similarly, Park (2005) observes that Japanese aggregate stock prices rose far more rapidly than dividends during the 1980s and hence temporarily broke down the cointegrating relationship between the log of prices and log of dividend during March – December, 1985. A recent paper by Gabriel and Martins (2011) shows that there is evidence of structural changes in the price-dividend relationship for the U.S. and Sweden but there is not for the U.K. The interesting part of this paper is that they model the cointegration test, which allows multiple structural breaks in the cointegration relationship, using Markov's switching model. Surprisingly, they show that when there are multiple breaks in data or that the data follow a non-linear Markov switching process, the traditional cointegration tests perform reasonably. However, in

\textsuperscript{1}See the discussion about structural change in the cointegration relationship in Chapter 2.
a single deterministic permanent shift, it is more likely that the residuals will exhibit a unit root process. In sum, they conclude that more frequent switching is less problematic than the one permanent shift.

Even though the issue of model or parameter instability has attracted considerable interest in the empirical studies, the structural stability of the predictive regression models of stock returns has received limited attention in the extent literature, especially using non-U.S. data. Instead of the formal structural break test, the structural change is typically handled by either trimming the sample period or estimating the predictive regression models for various subsamples. The issue of parameter instability or structural break both in the mean of the predictor and in the cointegration relationship is very important, as it invalidates the classical assumption of linear regression. Moreover, the inadequate power of the unit root test to discriminate the real unit root process and stationary process with a structural break may yield misleading results. This problem is relevant for predictive regression because a nonstationary property may characterize the financial variables used as a predictor. By neglecting the presence of structural change in the data, there exists an effect on the statistical inference of the test statistics, as noted by Bai (1997). Therefore, proper structural break tests should be performed in order to locate the accurate break(s) in the data, and then the information about the structural break should be carefully taken into account when estimating the models.

3.3 Econometric Methodology

In this chapter, the main idea is based on the structural break test and the process of taking such information into account when estimating the predictive regression. There are two main methods of dealing with the structural break. If the break date is exactly known, the Chow test can be employed. The Chow test tries to fit the same ARMA model to the pre-break data and post-break data. If neither model is significantly different, it can be concluded that there is no break in the data. Instead of the Chow test, a dummy variable can be used to represent the break date in the data. More specifically, if the break is suspected to occur after period \( t_m \), the dummy
variable $D_t$, such that $D_t = \begin{cases} 1, & t \leq t_m \\ 0, & \text{otherwise} \end{cases}$, must be created. Then, the following models are estimated to check the significance of $D_t$ in the regression.

$$y_t = \beta_0 + \alpha_0 D_t + \alpha_1 y_{t-1} + \varepsilon_t$$  \hspace{1cm} (3.1)

$$y_t = \beta_0 + \alpha_0 D_t + \alpha_1 y_{t-1} + \alpha_2 D_{t-1} + \varepsilon_t$$  \hspace{1cm} (3.2)

Equation (3.1) tests for a break in the intercept, while the equation (3.2) tests for a break both in the intercept and the coefficient.

However, the Chow test is not operational if the break date is not known. In reality, it is difficult to determine a certain break date in the financial data. A break occurring without being pre-specified by researcher is called an endogenous break. Intuitively, the Chow test can be performed for every potential break date $t_m$ in order to detect a break anywhere in the sample and the break date is located where there is the largest F-statistic. One thing that should be borne in mind is the number of observations. The trimming variable in each of the two subsamples must be large enough; otherwise the test statistics will be invalidated. Moreover, the distribution of F-statistics is not standard and cannot be obtained from the traditional $F$-table. Based on these processes, Andrews (1993) developed tests for parameter instability and structural change with one unknown change point. In addition, he simulates the asymptotic critical values for the F-statistics given the trimming value. Later on, these tests were extended to more than one unknown break point. Among others, the most popular one is Bai and Perron’s (1998) test. In particular, they extend this approach to perform an F test of no break against $\ell$ breaks and $\ell$ breaks against $\ell + 1 + 1$ breaks, respectively, with an arbitrary but fixed $\ell$.

Based on the linear regression with $m$ possible breaks, the least squares estimates of $\beta_j$ can easily be obtained from

$$y_t = \alpha_x \beta_j + \varepsilon_t, \quad t = t_{j-1} + 1, \ldots, t_j, \quad \text{and} \quad j = 1, \ldots, m + 1.$$  \hspace{1cm} (3.3)

Then, the minimal residual sum of the squares in each $j^{th}$ segment is calculated and summed together as follows:

$$RSS(t_{j-1}, t_j) = \sum_{j=1}^{m} RSS(t_{j-1} + 1, t_j).$$  \hspace{1cm} (3.4)

The breakpoints $t_{j-1}, \ldots, t_m$ are the global minimum of the following objective function,
Note that the global minimum location in equation (3.5) was obtained by an extensive grid search with order $O(n^m)$. However, searching for the most likely break date requires a large computation time. Fortunately, Bai and Perron (2003) propose a dynamic programming algorithm in an OLS regression based on Bellman’s principle. This makes computation easier and less time consuming.

Bai and Perron (1998) developed two statistics, the double maximum statistics or UDmax and WDmax in particular, for testing the null hypothesis of no structural breaks against the alternative hypothesis of an unknown number of breaks given an upper bound, $m$. Similarly, the $\text{SupF}(0 \mid \ell)$, which is a series of Wald tests for the hypothesis of no break against $\ell$ breaks, should be considered. In addition, if these tests show evidence of at least one break, Bai and Perron (1998) specify what they label the $\text{SupF}_T(\ell + 1 \mid \ell)$ statistic to test the null hypothesis of $\ell$ breaks against the alternative hypothesis of $\ell + 1$ breaks. Specifically, the $\text{SupF}_T(\ell + 1 \mid \ell)$ is used to check whether an additional break leads to a reduction in the sum of squares residuals. The advantage of Bai and Perron's (1998) test is that it allows for general specifications when computing test statistics and confidence intervals for the break dates and estimated coefficients. The test is also robust in terms of autocorrelation and heteroscedasticity in the regression residuals.

Therefore, to qualify the purpose of this chapter, the unknown multiple break dates proposed by Bai and Perron (1998, 2003) are an obvious candidate. Specifically, the Bai and Perron’s (1998, 2003) test using the GAUSS code provided in Pierre Perron’s (2004) home page together with the package ‘strucchange’ in the R program were employed in this chapter.

### 3.4 Empirical Evidence

#### 3.4.1 Data and Descriptive Statistics

The data comprise aggregate monthly closing stock prices $(P)$ and the aggregate monthly dividend-price ratio $(DP)$ on the Stock Exchange of Thailand index (SET index). The data were obtained from the Stock Exchange of Thailand and
cover the period from the beginning of the stock market, 30 April 1975, to 31 August 2011. The variables in small letters represent a logarithm form. Table 3.1 presents the descriptive statistics for the variables used in this chapter, the log dividend-price ratio in particular. In addition, the unit root tests are reported in Table 3.2.

As can be seen in Table 3.1, the log dividend-price ratio is a very persistent process. Nevertheless, the degree of persistence is reduced when the log dividend-price ratio is adjusted by its own sub-sample mean, as suggested by Lettua and Nieuwerburgh (2008). In addition, as tested in Chapter 2, the log dividend-price ratio has a unit root and is nonstationary. But when performing the Zivot and Andrews (1992) test, which is the unit root with endogenous break test, the null hypothesis of no unit root failed to reject. This finding implies that there is a structural break in the log dividend-price ratio and when such break is considered, the log dividend-price ratio has no unit root and becomes stationary. Furthermore, if the log dividend-price ratio is adjusted by its subsample mean, the adjusted series would have a stationary property.

**Table 3.1** Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD.</th>
<th>Skewness</th>
<th>$\rho_1$</th>
<th>$\rho_{12}$</th>
<th>$\rho_{24}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Dividend-price ratio (dp)</td>
<td>-3.264</td>
<td>0.598</td>
<td>-0.321</td>
<td>0.983</td>
<td>0.748</td>
<td>0.527</td>
</tr>
<tr>
<td>Adj. Log Dividend-price ratio (dp)</td>
<td>$6.57 \times 10^{-5}$</td>
<td>0.382</td>
<td>-1.149</td>
<td>0.959</td>
<td>0.464</td>
<td>0.016</td>
</tr>
</tbody>
</table>

**Note:** Sample Period: Apr 1975 - Dec 2010, 429 Monthly Observations

---

2 For details about the variable construction, please see Section 2.4.1 in Chapter 2.
3 The test to locate the structural break is performed in Section 3.4.3.
Table 3.2 Unit Root Tests Analysis Using Level Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF test</th>
<th>PP test</th>
<th>KPSS test</th>
<th>ZA test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Dividend-price ratio (dp)</td>
<td>-2.384</td>
<td>-2.227</td>
<td>1.234***</td>
<td>-5.097**</td>
</tr>
<tr>
<td>Adj. Log Dividend-price ratio ((\tilde{dp}))</td>
<td>-3.495***</td>
<td>-3.287**</td>
<td>0.174</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: *, **, *** Denotes 10%, 5%, and 1% Significant Level, Respectively.

3.4.2 Structural Break in the Log Dividend-Price Ratio

The standard specification of returns and predictive variables assumes that all variables have a stationary process around a constant mean. However, there is evidence that the log dividend-price ratio is nonstationary and is very persistent. For example, McMillan (2007) confirms that the financial ratio, the dividend-price ratio and earning-price ratio in particular, fluctuates around a changing level and does not exhibit a mean reversion to a single point. He concludes that such dynamic behavior may be caused by the presence of a structural break within the series. Similarly, evidence from Chapter 2 shows that the log dividend-price ratio is stationary when allowing for structural break as confirmed by Zivot and Andrew's test. Therefore, this section focuses on the behavior of the mean of the dividend-price ratio, the shift in the mean in particular, which invalidates the basic classical regression assumptions and renders the forecasting relationship unstable if such shifts are not taken into account.

The plot of the log dividend-price ratio with its full-sample mean is shown in Figure 3.1 on the left panel. Obviously, before 1988, the log dividend-price ratio was above the full-sample mean, whereas the ratio stays lower than the full-sample mean onwards. Even two decades later, the ratio still did not move back to its previous level. Thus, there is a sign that the log dividend-price ratio does not exhibit a mean reversion and is subject to a structural break.
Table 3.3  Bai and Perron's Double Maximum and $\text{SupF}_{T(\ell + 1|\ell)}$ Statistics for Tests of Multiple Structural Breaks in the Mean of the Log of Dividend-Price Ratio

Panel A: Test of structural breaks

<table>
<thead>
<tr>
<th></th>
<th>$\text{SupF}_{T(1)}$</th>
<th>$\text{SupF}_{T(2)}$</th>
<th>$\text{SupF}_{T(3)}$</th>
<th>$\text{UDmax}$</th>
<th>$\text{WDmax}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>26.598***</td>
<td>36.599***</td>
<td>43.816***</td>
<td>43.816***</td>
<td>70.899***</td>
</tr>
</tbody>
</table>

Panel B: Number of breaks selection

|                | $\text{SupF}_{T(2|1)}$ | $\text{SupF}_{T(3|2)}$ | Sequential | BIC | LWZ |
|----------------|----------------------|----------------------|------------|-----|-----|
|                | 5.556                | 9.1641               | 1          | 3   | 3   |

Source:  Bai and Perron’s, 1998.

Note:  *,**,*** Denotes 10%, 5%, and 1% Significant Level, Respectively.

In order to locate the shift in the mean of the dividend-price ratio, Bai and Perron’s (1998, 2003) test was then applied. The null hypothesis of no break against the alternative of $m$ breaks was investigated. Because of the limited sample size (429 monthly observations or about 35 years in total), the maximum numbers of break was set equal to 3 breaks. In addition, as commonly used, the trimming value was set equal to 10%, which means that at least 10% of the observations (about 50 months or 4 years) are in each of two subsamples.

The strategy recommended in Bai and Perron (2003) is strictly followed to identify the number of structural breaks. First, the double maximum statistics are calculated to determine if any structural breaks are present. If the double maximum statistics are significant, then the sequences of $\text{SupF}_{T(\ell + 1|\ell)}$ statistics are examined to decide the number of breaks.
Firstly, Panel A of Table 3.3 reports that both double maximum statistics are significant at conventional levels. Moreover, the $\text{SupF}_T(m)$ tests of null of no break against the alternative of $m$ break(s) are strongly rejected at the 1% level. In sum, the data seem to strongly favor a structural break(s) in the mean of dividend-price ratio rather than zero. Next, in order to select the number of breaks, a common procedure is to consider an information criterion. However, the BIC and LWZ always choose a much higher value than the true one in the presence of a serial correlation case, as documented by Bai and Perron (2003). Therefore, they suggest the method based on the sequential application of the test, which is superior to the information criterion. Table 3.3 Panel B reports that $\text{SupF}_T(2|1)$, which tests the null hypothesis of one break against two breaks, is insignificant at the conventional level. This indicates that there is only one break in the data. Therefore, the does not need to be considered, as suggested by Bai and Perron (2003). In sum, the one break case according to sequential test selection is mainly considered.

Table 3.4 shows the estimated mean of the log of dividend-price ratio in each regime. In the one break case, the mean of regime 1 is -2.600, which is higher than the full sample mean (-3.264), while the mean of regime 2 falls to -3.583. The means of other regimes corresponding to the case of two- and three-break are also displayed in Table 3.4. An obvious conclusion can be drawn—that the mean in regime 1, dated between 1975 and 1986, is relatively higher than that of other regimes. The plots of the dividend-price ratio with a full-sample mean and each regime mean are shown in Figure 3.1. Obviously, before 1988, the log dividend-price ratio was above the full-sample mean, whereas the ratio stays lower than the full-sample mean onwards.
### Table 3.4 Log of Dividend-Price Ratio and Breakpoint(s) Properties

<table>
<thead>
<tr>
<th>Regime 1</th>
<th>Regime 2</th>
<th>Regime 3</th>
<th>Regime 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.600 (0.032)</td>
<td>-3.583 (0.022)</td>
<td>-2.607 (0.029)</td>
<td>-3.714 (0.024)</td>
</tr>
<tr>
<td>-2.607 (0.029)</td>
<td>-3.714 (0.024)</td>
<td>-3.282 (0.038)</td>
<td></td>
</tr>
<tr>
<td>-2.600 (0.027)</td>
<td>-3.480 (0.034)</td>
<td>-3.913 (0.031)</td>
<td>-3.324 (0.032)</td>
</tr>
</tbody>
</table>

**Notes:** The first number in each cell is the estimated mean for such regime; standard error is reported in parentheses. The break date (end date of the regime) is on the second line, with 95% confidence intervals reported in brackets. The first regime begins in 1975:04 and the last regime ends in 2010:12.

In addition, the estimated break date is also reported with a 95% confidence interval. In the one break case, the break date is October 1986 and the 95% confidence interval is between March 1983 and October 1986.

#### 3.4.3 The Adjusted Dividend-Price Ratio

Lattua and Nieuwerburgh (2008) summarize that in the presence of structural breaks, a nonstationary dividend-price ratio is not a well-defined predictor and this causes an unstable forecasting relationship between returns and the dividend-price ratio over time. Therefore, they suggest that the dividend-price ratio must be adjusted to remove the nonstationary component (induced by the structural break) to render a stationary process.

In Section 3.4.2, there is strong empirical evidence in favor of change, one break in particular, in the log dividend-price ratio. I then follow Lattua and
Nieuwerburgh's (2008) framework to construct the adjusted log dividend-price ratio. Specifically, once the exact break date is located, the subsample means of the log dividend-price ratio are computed. In the one-break case with the break date \((\tau = 1986:10\text{ in my case})\), the adjusted log dividend-price ratio is calculated from

\[
\tilde{dp}_t = \begin{cases} 
  dp_t - \bar{dp}_1 & \text{for } t = 1, \ldots, \tau \\
  \bar{dp}_1 - \bar{dp}_2 & \text{for } t = \tau + 1, \ldots, T
\end{cases}
\]

where \(\bar{dp}_1\) is the sample mean for 1975:04 – 1986:10 and \(\bar{dp}_2\) is the sample mean for 1986:11 – 2010:12. The adjusted log dividend-price ratio in the two-break case could be defined analogously.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{LNTH_DP.png}
\caption{Change in the Mean of the Dividend-Price Ratio}
\end{figure}

Figure 3.1 shows the log dividend-price ratio and the adjusted log dividend-price ratio from April 1975 to December 2010. The left panel plots the log dividend-price ratio (solid dotted-line) with the full-sample mean (thin line), while the right panel plots the adjusted log dividend-price ratio (thin dotted-line) with the sub-sample mean, \(\bar{dp}_1\) and \(\bar{dp}_2\) (thin line). Notably, the adjusted series is rescaled so that it coincides with the adjusted series for the first sub-sample.

Now, comparing the descriptive statistics of the log dividend-price ratio and adjusted log dividend-price ratio, according to Table 3.1, although log dividend-price ratio has a unit root process, the adjusted log dividend-price ratio does not have a unit root process and is no longer nonstationary. The ADF and PP test statistics are
rejected at a 1% significance level with a value of -3.495 and -3.287, respectively. In addition, the KPSS test statistics of 0.174 failed to reject the null hypothesis of stationary properties. As is well known, the log dividend-price ratio is very persistent. In contrast, the adjusted log dividend-price ratio is much less persistent, with the first- and second-order autocorrelations of 0.945 and 0.403, respectively. Moreover, the adjusted log dividend-price ratio is less volatile than that of the log dividend-price ratio; the standard deviation of the former is dropped by half of the latter. Such findings are parallel with those reported in Lattuca and Nieuwerburgh (2008).

### 3.4.4 Predictive Regression with Adjusted Log Dividend-Price Ratio

Turning to the main objectives of this chapter which are to compare the results between the predictive regressions when a structural break in the predictive variable is considered and that is not considered. Specifically, this chapter compares the predictive regression between the returns equation and dividend growth equation using the log dividend-price ratio (referring to no break case) and the adjusted log dividend-price ratio (referring to one break case).

The stock returns and dividend growth predictive regression are based on the concept of the error correction model (ECM). So, equations (2.9) and (2.10) in Section 2.3 are rewritten as follows:

\[
\Delta \Pi_{t+k} = \rho_f (d_{t} - \Pi_{t}) + \varepsilon_{\Pi_{t+k}}. \tag{3.6}
\]

\[
\Delta d_{t+k} = \sigma_f (d_{t} - \Pi_{t}) + \varepsilon_{d_{t+k}}. \tag{3.7}
\]

where \(\Delta r_{t+k} = r_{t+k}\) denotes long horizon stock returns over \(t + k\) horizons. Specifically, it is a cumulative return calculated from \(r_{t+k} = r_t + r_{t+1} + \ldots + r_{t+k}\). Similarly, dividend growth, \(\Delta d_{t+k}\), is calculated in the same way. For the predictive regressions, all historical value ranges from 1975:4 to 2010:12 (429 monthly observations) were used to estimate the model parameters. Moreover, the reason to consider the predictive horizon \((k)\) range from 1 to 60 months is to provide good insight into the predictive power of the log dividend-price ratio at various horizons. Under the null hypothesis, the log dividend-price ratio has no predictive power, i.e. \(H_0: r_F = 0\) and \(H_0: \sigma_F = 0\) for equation (3.6) and (3.7), respectively. The inferences about the significance of the log dividend-price ratio were drawn by examining the \(t\)-
statistic of $\theta_p$ and $\theta_d$ and were used as evidence for predictability. In addition, the goodness-of-fit statistic, $R^2$, was referred to as a measure on how the log dividend-price ratio can explain variation in the returns and dividend growth variables. It was to be noted that, since the overlapping observations were used, there was a possible serial correlation problem in the disturbance term which the standard OLS $t$-statistic does not account for. Therefore, in order to mitigate such problem, the Newey and West’s (1987) method to correct the standard errors was used. These standard errors are robust regarding the heteroscedasticity and serial correlation in the error term.

The results of the predictive regression using both log dividend-price ratio without any adjustment (no break case) and the log adjusted dividend-price ratio (one-break case) are reported in Table 3.5. The range of horizons in the predictive regressions begins from one year to five years to be consistent with Cochrane (2005).

Considering the predictive power of the regression over horizon for the case of no break, for the return predictive regression, the results show that the size of the estimated coefficients and R-squared has grown over the horizons with significant and corrected sign. However, the estimated coefficients from the dividend growth predictive regression are significant only for the first two-horizon. In addition, the estimated coefficients of dividend growth predictive regression from the longer horizon are smaller and insignificant. In sum, the results from the no break case support the long horizon predictability of returns by using the log dividend-price ratio and this can predict future returns better than the dividend growth. One must bear in mind that the log dividend-price ratio used in these predictive regressions is nonstationary; it is stationary with a structural break in particular. Therefore, a spurious regression can possibly occur.

Next, considering the results of the predictive regression with one structural break in the log dividend-price ratio, evidence that the size of the predictive coefficient increases over forecast horizon is still found, similar to those reported in Cochrane (2008). Moreover, the estimated coefficients from the one-break case are larger than those reported in the no break case. Such findings are similar to those of Lattua and Nieuwerburgh (2008). However, the estimated coefficients from the return predictive regression are marginally increased for the first three years and then decreased in four and five forecasting horizons. Unlike the return predictive
regression, the estimated coefficients from the dividend growth predictive regression present a very nice pattern; they grow over the horizons. In conclusion, once incorporating the information about the structural break in mean of the log dividend-price ratio using Lattua and Nieuwerburgh’s (2008) framework, the predictability of the predictive regressions through the log adjusted dividend-price ratio economically increases. Even though the results from the return predictive regression are not as strong as expected, the overall results show the importance of structural break information. Nevertheless, the adjustment technique suggested by Lattua and Nieuwerburgh (2008) implicitly assumes that the cointegration relationship between the log of price and log of dividend is (1, -1)’ and that there is no structural break in the cointegration relationship over time. However, evidence from Chapter 2 reveals that there is a structural break in the cointegration relationship between the log of price and log of dividend as confirmed by Gregory and Hansen’s (1996) test. Therefore, such evidence motivated me to further explore the alternative adjustment technique, which considers a possible structural change in the cointegration vector as well as the case where the cointegration coefficient is not equal to (1, -1)’ over time.

<table>
<thead>
<tr>
<th>Table 3.5 Predictive Regression of Log Returns and Log Dividend Growth with the Log Dividend-Price Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Horizon (years)</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
Table 3.5 (Continued)

<table>
<thead>
<tr>
<th>Horizon (years)</th>
<th>Returns</th>
<th>Dividend growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No break</td>
<td>One break</td>
</tr>
<tr>
<td>3</td>
<td>0.309</td>
<td>0.461</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.159)</td>
</tr>
<tr>
<td></td>
<td>[0.090]</td>
<td>[0.071]</td>
</tr>
<tr>
<td>4</td>
<td>0.334</td>
<td>0.351</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.206)</td>
</tr>
<tr>
<td></td>
<td>[0.081]</td>
<td>[0.031]</td>
</tr>
<tr>
<td>5</td>
<td>0.383</td>
<td>0.315</td>
</tr>
<tr>
<td></td>
<td>(0.153)</td>
<td>(0.216)</td>
</tr>
<tr>
<td></td>
<td>[0.087]</td>
<td>[0.019]</td>
</tr>
</tbody>
</table>

Notes: This table reports on the estimation results from equation (3.6) and (3.7). The first two columns report the equation for returns while the next two columns report the predictability equation for dividend growth. The point estimation is on the first line, the standard error is in the parentheses, and the R-square is reported in brackets. In the one break case, the dividend-price ratio is adjusted by each regime mean, as shown in Table 3.4.

3.4.5 Predictive Regression Using Disequilibrium Errors from the Cointegration Regression

The results in Section 3.4.4 cast doubt about the ability of the log dividend-price ratio in return predictive regression, especially when compared with the dividend growth predictive regression. Even allowing for a possible structural break in mean of the log dividend-price ratio, the results are marginal and still do not
strongly favor return predictive regression. However, as discussed above, the results in the previous section are based on the implicit assumption that there is only a shift in the mean of the dividend-price ratio, while the cointegrating relationship between the log of prices and log of dividend is \((1, -1)\)', as suggested by Campbell and Shiller (1988).

Recalling the cointegration test in Chapter 2, there is no cointegrating relationship between the log of price and log of dividend in Stock Exchange of Thailand. In addition, once a possible structural change in the cointegrating relationship is allowed, the null hypothesis of no cointegration is rejected. Therefore, there is strong evidence to support the idea that there exists a structural change in the cointegrating relationship between the log of price and log of dividend, and the corresponding break is on October 1986. This result indicates that the cointegrating coefficients are not stable over time. Then, the cointegration relationship in two subsamples; pre- and post-break dates, are estimated. The results show that the cointegration coefficients are 0.58 and 0.55, respectively. In addition, whereas the cointegration coefficient from whole sample is 0.96 and is insignificantly different from one, the cointegration coefficients from the subsamples significantly drop about half and they are all significantly different from one. This implies that the cointegration relationship is not stable over time or during the subsample period; the cointegration relationship between the log of prices and log of dividend is not equal to one-by-one, as mentioned by Campbell and Shiller (1988). Therefore, proper adjustment should be considered to take such information into account.

In particular, the log price-dividend ratio (the reciprocal of log dividend-price ratio) is transformed by its cointegration coefficient. Specifically, in order to take the instability of the cointegration coefficient and the fact that it does not equal one into account, the disequilibrium error is used in the predictive regression. In other words, the log price-dividend ratio with the estimated cointegration coefficient is used as 

\[
p_d_t = p_t - 3.38 - 0.96d_t
\]

for the no break case, while the transformed log price-dividend ratio equal to 

\[
\tilde{p}_d_t = p_t - 3.56 - 0.58d_t
\]

is simply applied for the period before October 1986 and afterward 

\[
\tilde{p}_d_t = p_t - 4.85 - 0.55d_t
\]

Notably, this technique allows the series to be demeaned as well as to be adjusted by its corresponding cointegration coefficient. Fortunately, the transformed log price-
dividend ratio is a stationary process. Again, equations (3.6) and (3.7) are re-estimated using the transformed log price-dividend ratio and the results are reported in Table 3.6. Since the log price-dividend ratio is the reciprocal of log dividend-price ratio, the expected signs are opposite those in Table 3.5. In particular, a negative relationship is expected from return predictive regression while positive relationship is expected from dividend growth predictive regression using the log price-dividend ratio.

Not surprising, in the no break case, the estimated coefficients from the return predictive regression are significant in all horizons and grow over horizons with increasing R-squares. Similarly, the estimated coefficients from the return predictive regression in one-break case are larger than those of the no break case and significant in all horizons. Whereas the estimated coefficients grow over horizons as suggested by Cochrane (2005), the R-squares are quite stable over horizons. Overall, the results of the return predictive regression using the transformed log price-dividend ratio are impressive and I can conclude that the difference from the unity of the cointegration coefficient has a drastic effect on the predictive regression. In other words, the adjustment by the subsample cointegration coefficient considerably improves return predictability.

Table 3.6 Predictive Regression of Log Returns and Log Dividend Growth with the Disequilibrium Error from Cointegration Regression (Log Price-Dividend Ratio)

<table>
<thead>
<tr>
<th>Horizon (years)</th>
<th>Returns</th>
<th>Dividend growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No break</td>
<td>One break</td>
</tr>
<tr>
<td>1</td>
<td>-0.100</td>
<td>-0.491</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.102)</td>
</tr>
<tr>
<td></td>
<td>[0.030]</td>
<td>[0.173]</td>
</tr>
<tr>
<td>2</td>
<td>-0.251</td>
<td>-1.209</td>
</tr>
</tbody>
</table>
Table 3.6 (Continued)

<table>
<thead>
<tr>
<th>Horizon (years)</th>
<th>Returns</th>
<th>Dividend growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No break</td>
<td>One break</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.144)</td>
</tr>
<tr>
<td></td>
<td>[0.090]</td>
<td>[0.345]</td>
</tr>
<tr>
<td>3</td>
<td>-0.326</td>
<td>-1.364</td>
</tr>
<tr>
<td></td>
<td>(0.103)</td>
<td>(0.201)</td>
</tr>
<tr>
<td></td>
<td>[0.100]</td>
<td>[0.382]</td>
</tr>
<tr>
<td>4</td>
<td>-0.355</td>
<td>-1.346</td>
</tr>
<tr>
<td></td>
<td>(0.135)</td>
<td>(0.254)</td>
</tr>
<tr>
<td></td>
<td>[0.092]</td>
<td>[0.288]</td>
</tr>
<tr>
<td>5</td>
<td>-0.411</td>
<td>-1.470</td>
</tr>
<tr>
<td></td>
<td>(0.153)</td>
<td>(0.268)</td>
</tr>
<tr>
<td></td>
<td>[0.100]</td>
<td>[0.275]</td>
</tr>
</tbody>
</table>

Notes: This table reports the estimation results from equation (3.6) and (3.7). The first two columns report the equation for returns while the next two columns report the predictive equation for dividend growth. The point estimation is on the first line, the standard error is in the parentheses, and the R-square is reported in brackets. In the one break case, the change in the cointegrating relationship in particular, the price-dividend ratio is adjusted by its estimated cointegrating coefficient. Moreover, the log price-dividend ratio is the reciprocal of the log dividend-price ratio; hence the expected signs are negative for the return predictive regression and positive for the dividend growth predictive regression.
Looking at the dividend growth predictive regression in the no break case, it can be seen that the performance of the log price-dividend ratio is similar to that shown in Table 3.5. In particular, the estimated coefficients are significant only for the first two forecasting horizons. In addition, for the one-break case, the transformed log price-dividend ratio does predict dividend growth only for the first two years. However, for longer forecasting horizons, there is no predictability of the transformed log price-dividend ratio in the dividend growth predictive regression, and worse, the estimated signs are wrong. Similarly, Campbell (2003) also finds that the significance of dividend growth is confined over relatively short horizons.

In general, this section finds that the adjustment technique using the cointegration coefficient or using the disequilibrium error from the cointegration regression provides impressive results. Compared to the previous return predictability using the nonstationary log dividend-price ratio and log adjusted dividend-price ratio, the stock return predictability by the transformed log price-dividend ratio or disequilibrium error from the cointegration regression improves even further. In addition, the transformed log price-dividend ratio is better in predicting the return rather than the dividend growth. The results are similar to those in Lee (2004).

3.5 Conclusion

The present value model of stock prices implies that the log of prices and log of dividend are cointegrated and hence the log dividend-price ratio is able to predict either the changes in future prices or the changes in future dividends. However, the log dividend-price ratio may not be an appropriate predictor unless the log of prices and log of dividend are cointegrated with the cointegrating vector \((1, -1)\). In addition, the predictability of the predictive regression depends on not only whether the log dividend-price ratio has a cointegrating vector \((1, -1)\), but also whether the predictive relationship is stable. Failure to detect and account for structural change is known to be a serious model misspecification which adversely affects statistical inferences and generally leads to poor predictive performance. Indeed, the instability issue is especially relevant to cointegration analysis since it normally involves long spans of data which are likely to exhibit structural breaks.
Evidence of a structural break in the cointegration relationship from Chapter 2 motivated me to further investigate the effect of such instability in the predictive regression. Therefore, a formal structural break test was performed to examine a possible shift in the mean in the log dividend-price ratio. Using Bai and Perron’s (1998) structural break test, there was one break located on October 1986. The existence of a structural break in the predictor violates the assumptions of the standard regression and invalidates the first order asymptotic distribution of the test statistics. Lattua and Nieuwerburgh (2008) summarize that in the presence of structural breaks, a nonstationary dividend-price ratio is not a well-defined predictor and this causes an unstable forecasting relationship between returns and the dividend-price ratio over time. Therefore, they suggest that the dividend-price ratio must be adjusted to remove the nonstationary component (induced by the structural break) to render a stationary process. Once the log dividend-price ratio was adjusted according to Lattua and Nieuwerburgh's (2008) framework, the results of the predictive regressions using the nonstationary log dividend-price ratio (or stationary with a structural break log dividend-price ratio) and log adjusted dividend-price ratio were compared and were reported in Table 3.5. In particular, there are two main findings: first, predictability using the adjusted log dividend-price ratio improves, and second, the adjusted log dividend-price ratio is better in predicting returns rather than dividend growth. Even though the results from the return predictive regression are not as strong as expected, the overall results show the importance of structural break information.

However, the adjustment technique suggested by Lattua and Nieuwerburgh (2008) implicitly assumes that the cointegration relationship between the log of price and log of dividend is \( (1, -1)' \) and is stable over time. Recalling the evidence of structural change in the cointegration relationship from Chapter 2, I further split the data into two subsamples and re-estimate the cointegration coefficient in each subsample. Not surprising, the cointegration coefficient in each subsample is significantly less than one and significantly different from each other. This implies that the long run relationship between the log of prices and log of dividend in each subsample does not move as theory has suggested. Indeed, their movement is not one-by-one and hence an appropriate adjustment is required. The disequilibrium error from the cointegration regression is:

\[
\tilde{pd}_t = p_t - 3.56 - 0.56d_t, \quad \tilde{pd}_t = p_t - 4.85 - 0.55d_t.
\]
for transformed log price-dividend ratio before October 1986 and after October 1986, respectively, was used as a predictor. Overall, the adjustment technique using the cointegration coefficient or using the disequilibrium error from the cointegration regression provide impressive results. Moreover, once compared to the previous return predictability using the nonstationary log dividend-price ratio and log adjusted dividend-price ratio, the stock return predictability by the transformed log price-dividend ratio or disequilibrium error from the cointegration regression improves even further. Finally, I can conclude that the return predictability is strong, as suggested by theory, once the information about the structural break in the mean of the predictor, the structural break in the cointegration relationship, and the evidence that the cointegrating coefficient is not equal to one are taken into consideration. In other words, this finding can possibly explain the weak evidence of return predictability in past literature, in which those models are misspecified.
CHAPTER 4

THE PERMANENT AND TRANSITORY COMPONENT OF STOCK PRICES AND RETURN PREDICTABILITY IN VECTOR AUTOREGRESSION (VAR) ANALYSIS

4.1 Introduction

In the random walk hypothesis, changes in stock prices are explained only by unexpected shocks and stock returns are unpredictable. In this view, shocks in prices provide permanent effects, which do not dry out over time. On the other hand, if stock prices follow mean-reversion process, shocks to prices have only transitory effects. Therefore, impacts of shocks will gradually decrease over time.

Many empirical studies have attempted to differentiate mean-reversion and random walk properties in stock prices. For example, Fama and French (1988) provide empirical evidence of mean reversion in U.S. stock prices and a negative serial correlation in stock returns using univariate time series regression. In that case, stock prices do not follow random walk process, which implies predictability in returns. Fama and French (1988) propose that this result could be explained by effects of permanent and temporary components in stock prices. Other papers, e.g. Poterba and Summers (1988) also find similar results that stock prices are affected by more than one type of disturbance.

Later, Cochrane (1994) has extended this issue into a multivariate framework using the Vector Autoregression (VAR) model. In this framework, both stock prices and dividends are considered as endogenous variables. Therefore, the time paths of each variable are concurrently affected by the sequences in other variables. The estimated regressions in the VAR model provide information about the relationship between prices and dividends, as suggested by the present value model. Subsequently, the dynamic responses of both prices and dividends to shocks in each equation, i.e.
Impulse Response Function (IRF), can be computed. In addition, an interpretation of the interrelationships among the variables in the VAR system can be done by using (forecast error) Variance Decomposition (VD), which represents the proportion of fluctuation in each series due to its own innovation and innovations in other series in the system. Using this methodology, Cochrane (1994) finds that both stock prices and dividends move toward their new long-term equilibrium value quickly after a shock in dividends. Though, a price shock had a minimal effect on dividend and, holding dividends constant, the stock price responses to its own disturbance is dried out completely over time. Moreover, the results of variance decomposition show that a large portion in the variance of returns could be attributed to a price shock, while variation in dividends stems mostly from its own innovation. Therefore, Cochrane (1994) concludes that a price shock has a transitory effect on prices but has no effect on dividends. However, a shock to dividends has permanent effects on both prices and dividends themselves. This result implies that a dividend follows a random walk process, while stock returns are predictable.

In this chapter, the issue of permanent and transitory components in stock prices and dividends has been investigated using the VAR methodology. First, the unrestricted reduced-form VAR model is considered. Second, the Vector Error-Correction Model (VECM), which imposes the existence of cointegrating vector and error-correction mechanisms on the VAR model, is then estimated. Finally, the restrictions of transitory and permanent shocks are applied in the Structural VAR (SVAR) model. In each setting of the VAR model, the IRF and VD are computed to provide a conclusion about the nature of each shock and factors that influence variations in prices and dividends. In addition, the Granger causality tests are carried out to assess the direction of relationship between stock prices and dividends.

The organization of this chapter is outlined as follows. In section 4.2, the development of empirical studies in response to permanent and transitory shocks in stock prices and dividends is carefully reviewed. Section 4.3 summarizes the econometric methodology of the VAR and VECM in the present value model of stock prices. The computation of the IRF and VD are also discussed in this section. The empirical results are shown in section 4.4, and section 4.5 concludes this chapter.
4.2 Literature Review

Empirical studies on return predictability usually focus on either the behavioral characteristics of stock prices and returns in univariate analysis or predictive regressions with fundamental variables that help to explain fluctuation in stock returns (Crowder and Wohar, 1998). The first group of studies (e.g. Fama and French, 1988, Lo and McKinley, 1988) focus on the mean reversion component in stock prices and the results usually showed that stock prices follow a more general form of non-stationary rather than a random walk process. Summers (1986) initially explains the general form of the non-stationary process with the hypothesis that there are two components of stock prices, i.e. random walk $q(t)$ and stationary process $z(t)$.

\begin{equation}
q(t) = q(t-1) + \mu + \eta(t),
\end{equation}

\begin{equation}
z(t) = \varphi z(t-1) + \varepsilon(t),
\end{equation}

where $\mu$ is expected drift, $\eta(t)$ is a white noise and $z(t)$ follows a first-order autoregression, $AR(1)$, with $\varphi$ close to but less than one.

Summers (1986) elaborates that stock prices may take long temporary swings from their fundamental value (permanent component) and slowly revert to a long-term equilibrium path. To be more specific, suppose that there is a positive temporary shock to the current stock price. One would expect the current stock price to rise above what it should be in absence of such a shock; hence, the current stock returns would be greater than the long-run mean. Since a stationary shock is expected to fade away in the long run, stock prices eventually decline to their normal levels, which are dominated mainly by the fundamental component. Therefore, this process induces a negative autocorrelation in long-term stock returns. However, the slow decay of a temporary component which introduces a negative autocorrelation in returns is difficult to detect using a short span of data. Fama and French (1988) confirm this interpretation by regress overlapping multi-year returns using the univariate autoregressive model of stock returns. They detect a significant negative autocorrelation in returns series, which supported the hypothesis that stock prices do not follow a random walk process. In addition, the size of this autocorrelation coefficient is close
to -0.5, especially for a 3- to 5-year return period, suggested in a hypothesis that combines between permanent and temporary shocks in stock prices.

The second group of studies is based on using predictive variables to explain fluctuation in stock returns. Empirical evidence of return predictability has been documented in many studies, e.g. Campbell (2001) and Cochrane (2005). Details of the predictive regression on stock returns using the dividend-price ratio as a predictive variable and a review of the literature of this research area have been discussed in Chapters 2 and 3. However, the predictive regression approach has been criticized in many aspects. In addition to the instability in predictive regression, as addressed in Chapter 3, the endogeneity problem in predictive regression is also pointed out in Stambaugh (1986). To account for such a problem, the system of equation approach is proposed to estimate the predictive system. Campbell, Lo, and MacKinlay (1997) have addressed the advantage of using the VAR approach, which estimates the regressions in the system, simultaneously. Therefore, all of the variables are treated equivalently as endogenous variables. However, the predictive performance of the VAR model is based on how to put the structure of relationship on such a system. Hodrick (1992) summarizes that once the structure of the VAR system is correctly specified, the corresponding result of the VAR is better than that of long-horizon predictive regressions.

Cochrane (1994) has applied the VAR framework to investigate the long-term relationship between stock prices and dividends, as well as stock returns and dividend growth predictability. The VAR model allows for the specification that every variable in the system is set as an endogenous variable. Therefore, the dynamic behaviors in each variable can be influenced by error terms of all regressions in the system. He also suggests that the effects of permanent and temporary shocks on stock prices can be investigated in the VAR model using the impulse response analysis and forecast error variance decomposition. The estimation of the VAR is based on the system that consists of first differences in log-dividends and log-prices. The lagged terms of both variables and the dividend-price ratio are used as explanatory variables. This specification represents the Vector Error-Correction Model (VECM), where the dividend-price ratio is used as a proxy for a common trend in the long-term relationship between prices and dividends. The predictive regressions from each of
the VECM regressions show that the dividend-price ratio is a better predictor of return forecast than of dividend growth. Moreover, the $R^2$ of the return regression is higher than that of dividend growth. The IRFs provide a pattern by which dividends do not respond to a price shock but are responsive immediately to their own innovation and do not converge to their previous level. For stock prices, the reactions are also different between shocks in price and dividend. An innovation in a dividend provides similar impacts between prices and dividends, as stock prices react quickly and the effects of shocks are not dried out (permanent). However, a price stock (holding the dividend constant) provides immediate responses in stock prices that gradually decrease over time. The effects are computed to be a complete transitory effect as prices tend to convert to their original level before a shock. The results of the variance decomposition show that more than half of the variances of returns can be explained by a price shock, which is transitory. This result supports the explanation that return predictability comes from the transitory component in stock prices. The permanent shock’s component, which comes from the response of prices to dividends, explained 47 percent of the variation in prices. For dividends, most of their variations (99 percent) are attributed to their own innovation. Therefore, Cochrane (1994) concludes that stock returns are predictable. In other words, the adjustment of stock prices under the error-correction process has moved the dividend-price ratio back to its long-term equilibrium value.

Lee (1995) also focuses on the response of stock prices to permanent and temporary shocks and has extended the model to the case that the dividend process is the sum of permanent and temporary components. Specifically, the VAR model of stock prices and the price-dividend spread is employed with the restriction on the Bivariate Moving-Average Representation (BMAR). This restriction is used to identify the two types of shocks in dividends. Variance decomposition is then applied to measure the relative impact of each component on the variation in stock prices, and IRFs are calculated to investigate the dynamic response of each shock to stock prices. To do that, Lee (1995) carefully applies Blanchard and Quah’s (1989) identification procedure in setting the restriction and in separating the effects of the permanent and transitory shocks. The results of the variance decomposition show that stock prices respond significantly to both permanent and temporary shocks in dividends.
Therefore, substantial variation in stock prices is due to the temporary shocks. In conclusion, he interprets his findings as a result of an imperfect information hypothesis, in which investors fail to distinguish between two components in dividends. Such evidence provides an alternative explanation for mean-reverting property in returns to Cochrane (1994), who explains that a majority of the variation in stock prices is due to a temporary shock in the stock price itself (discount rate shock).

Lee (1998) has extended the study to cover different types of shocks including permanent and temporary changes in earnings and dividends, and changes in discount factors and non-fundamental factors. Using Blanchard and Quah’s (1989) restriction under the Structural VAR (SVAR) framework, he has found that the time-varying excess returns represent the risk premium and account for most of the variation of stock prices during the postwar period, while the long-term trend in stock prices is due to permanent changes in the fundamental, i.e. earnings and dividends. Moreover, the non-fundamental factors account for a small portion of the variance in stock prices. Such findings also support the evidence for return predictability by variation in the discount factors.

Crowder and Wohar (1998) use both the VAR and VECM models to investigate the responses of stock prices to permanent and transitory shocks. However, the identification procedure is different from that of Lee (1995, 1998). In particular, they apply the cointegration test and the VECM to investigate shocks in the stock price and dividend regressions of the VAR model. Their results show that stock prices and dividends have a long-run cointegration relationship but the dividends do not respond to the spread between prices and dividends. Therefore, dividends can be treated as an exogenous variable in the system and shocks in the dividend can be identified as a permanent component while innovations to stock prices must be classified as a transitory component. Their IRFs are similar to those of Cochrane (1994). Specifically, shock in dividends causes both prices and dividends to increase permanently. The IRF of the price-dividend ratio quickly varnishes as the stock price adjusts to its new long-term equilibrium in approximately 14 quarters. However, shock in stock prices has no significant long-run effect on either stock prices or dividends.
Therefore, this chapter focuses on the long-term equilibrium between stock prices and dividends as suggested in the present value model using the VAR framework. The effects of permanent and transitory shocks are identified in both the VAR and VECM. First, I follow Cochrane (1994) by estimating the bivariate model of returns and dividend growth. The IRFs and VDs are then computed. Next, the cointegration test is applied. The VECM is estimated to account for the presence of cointegration relationship. IRFs and VDs are re-estimated using the VECM. Finally, the Structural VAR (SVAR) model with Blanchard and Quah’s (1989) restriction is used to compare the results with those of the VAR and VECM.

4.3 Vector Autoregression (VAR) Analysis in the Present Value Model of Stock Prices

The VAR methodology has been applied in empirical studies on the present value model of stock prices. Campbell and Shiller (1987) firstly introduce the VAR model for testing cointegration. Cochrane (1994) has used the VAR model and investigated return predictability using error-correction terms in the VECM. In addition, IRFs and variance decomposition are used to assess the impacts of permanent and temporary shocks on stock prices and dividends. Lee (1995) suggests that the Structural VAR (SVAR) can be applied to identify the effects of shocks between permanent and transitory shocks. Although this section provides a brief review of the VAR framework including the VECM, SVAR, IRF and the variance decomposition analysis, the present value model of stock prices is still used as the main theoretical background in this chapter.

4.3.1 The VAR Model in Structural and Reduced Form

The VAR model extends the dynamic multivariate regression into a system of equations. Let \( \mathbf{Y} \) be the vector of endogenous variables in the system. Consider the bivariate VAR system of logarithms of stock prices \( (p) \) and dividend \( (d) \), i.e., \( \mathbf{Y} = [p, d] \). The system of Autoregressive Distributed-Lag (ARDL) regression with one lagged term in each variable is set up as follows.
Equations (4.4) and (4.5) are called the structural form (or primitive system) of the VAR model, which can be written as the following system:

\[
\begin{bmatrix}
1 \\
0 \\
\end{bmatrix} Y_t =
\begin{bmatrix}
\beta_0 \\
\beta_1 \\
\end{bmatrix} + Y_{t-1} + \epsilon_t.
\]

A matrix form of this structural VAR system with one lagged in the vector of the endogenous variables, VAR(1), is expressed as follows:

\[
BY_t = A_0 + A_1 Y_{t-1} + \epsilon_t.
\]

In this setting, both \( p \) and \( d \) have contemporaneous effects on each other. However, such contemporaneous correlations lead to endogeneity problems in estimating each equation. Therefore, in the standard form of the VAR, the structural model is transformed into reduced-form equations by pre-multiplying \( B^{-1} \) into both sides of the equation (4.7). Therefore, the standard (reduced form) VAR model is shown as follows:

\[
Y_t = A_0 + A_1 Y_{t-1} + \epsilon_t,
\]

where \( A_0 = B^{-1} \beta_0 \), \( A_1 = B^{-1} \beta_1 \), \( \epsilon_t = B^{-1} \epsilon_t \).

Let \( a_{i,0} \) represent element \( i \) of vector \( A_0 \) and \( a_{i,j} \) represent the element in row \( i \) and column \( j \) of matrix \( A_1 \) and \( \epsilon_{i,t} \) be element \( i \) of vector \( \epsilon_t \). The equation (4.8) can be rewritten as a VAR in standard form as follows:

\[
P_t = a_{20} + a_{11} p_{t-1} + a_{12} d_{t-1} + \epsilon_{2t},
\]

\[
d_t = a_{20} + a_{21} d_{t-1} + a_{22} p_{t-1} + \epsilon_{2t}.
\]

It is important to note that the error terms in equation (4.9) and (4.10) consist of two shocks \( \epsilon_{1,t} \) and \( \epsilon_{2,t} \) or pure innovation (shocks) in \( p_t \) and \( d_t \), respectively. The error terms in equation (4.9) and (4.10) can be computed from

\[
\epsilon_{1,t} = (\epsilon_{1,t} - b_1 \epsilon_{2,t})/(1 - b_1 b_2),
\]

\[
\epsilon_{2,t} = (\epsilon_{1,t} - b_2 \epsilon_{2,t})/(1 - b_1 b_2).
\]

The estimation of the VAR system is typically based on the reduced-form model. The estimated coefficients provide a combination of the coefficients that related the dynamic response between variables in the structural form. In addition, the error terms also relate to more than one structural innovation (see equations (4.11) and (4.12)).
Therefore, the estimated coefficients in each equation of the reduced-form of the VAR model cannot be interpreted as a short-term and long-term relationship between prices and dividends. The identification of the model can be achieved by incorporating restrictions in the primitive system, e.g. the type of recursive system restriction of Sim (1980), and by recovering the structural form of VAR (Enders, 2009: 305-306).

4.3.2 Vector Error Correction Model (VECM)

In the VAR framework, Johansen’s (1988) cointegration methodology can be applied to test for the existence of cointegrating vectors between variables in the system using the (likelihood-based) rank test. In addition, the VAR model can be transformed to the Vector Error-Correction Model (VECM) by imposing the cointegrating vector and estimating the error-correction terms. The VECM provides information about long-term relationship (or common trend between variables) and adjustment process in each variable.

The estimation of the VECM begins with testing the existence of a cointegration relationship using the likelihood-ratio tests of Johansen (1988). The methodology of the likelihood-based rank test has been discussed in Chapter 2. Under the Granger representation theorem, when (at-least one) cointegrating vector is found, the VAR model in equation (4.8), can be written in the error-correction representation as follows;

\[
\Delta Y_t = \pi Y_{t-1} + \varepsilon_t
\]  

where \( \pi = A_1 - I \). The term \( \pi Y_{t-1} \), is referred to an error-correction component. The coefficient matrix \( \pi \) can be decomposed into vector of cointegrating vector, \( \beta = (\beta_1, \beta_2) \), and the vector of adjustment coefficients, \( \alpha = (\alpha_p, -\alpha_d) \).

In the bivariate system of the logarithm of prices and dividends, equations (4.9) – (4.10) can be written in error-correction mechanisms as follows;

\[ \Delta p_t = -\alpha_p (\beta_1 p_{t-1} - \beta_2 d_{t-1}) + \varepsilon_{p,t} \quad \alpha_p \gg 0, \]

\[ \Delta d_t = \alpha_d (d_{t-1} - \beta_1 p_{t-1}) + \varepsilon_{d,t} \quad \alpha_d \gg 0. \]

For the general form of VAR with \( p \) lags (VAR(\( p \))),

\[ Y_t = A_2 Y_{t-1} + A_3 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \]

the VECM is written as,
where \( \pi \) represents a matrix of error-correction coefficients and cointegrating vector, and \( \Gamma_i \) represent the short-term dynamic between each endogenous variable. In case that \( \pi \) is a zero matrix, the VECM becomes a standard VAR in the first difference and then a long-term equilibrium does not exist. However, when one or more elements in a \( \pi \) matrix does not equal zero, the movement pattern of a series can be explained by error-correction process. Therefore, estimating a VAR in the first difference does not appropriate because the omission of the error correction terms entails a miss-specification error (Enders, 2009: 367).

4.3.3 Impulse Response Functions and Variance Decomposition

In the VAR model, the dynamic multiplier of one variable to the others cannot be obtained directly from the estimated coefficients. The VECM representation can be used to explain the long term equilibrium and adjustment process but cannot be used to describe all of the dynamic mechanisms in the feedback relationship between each variable. Consequently, the impulse response and variance decomposition methodology are usually applied in empirical studies.

In the impulse response analysis, the reduced-form VAR model can be rewritten as a Moving-Average Representation (MAR) as follows;

\[
Y_t = \mu + \Phi_0 e_t + \Phi_1 e_{t-1} + \Phi_2 e_{t-2} + \ldots,
\]

where \( \Phi = (1 - A L)^{-2} \).

In this setting, the interaction between each time series sequences in a system can be examined using the sets of coefficients \( (\Phi) \) in a MAR. The IRF then is defined as the responses of the current and future values of each of the variables to a one unit (or one standard deviation) shock in the current value of error terms in the \( i^{th} \) equation of the VAR model \( (e_{i,t}) \). The IRF of a shock in the \( i \) equation can be computed from the element of \( i \) column \( \Phi_{i,k}(j) \) and is usually displayed as a graph between these coefficients against time period \( (j) \). The sign, size and timing of the response are used to provide information about dynamic of multipliers between the variables in the system.
Similar to the transformation of a reduced-form VAR into a primitive form, the conversion of coefficients in the VAR model to the MAR also has an identification problem. Hence, additional restrictions are required in order to classify the impulse responses. For this purpose, Cholesky decomposition is usually used. In Cholesky decomposition, the contemporaneous response between variables in the VAR system is set in an asymmetric way where some variables are allowed to respond to shocks in other variables in the same time but not vice versa. In this concept, there is one variable that is allowed to respond contemporaneously to shocks in every variable in the system and another has no immediate response to any shocks (except shocks in its own equation). The other variables are set to be an ordering of the variables based on asymmetry in the direct instant effects on each other.

In the case of the bivariate system of the present value model of stock prices $Y = [p, d]$, suppose that the dividend is ranked first, follow by the prices. Cholesky’s ordering implies that prices will contemporaneously move with dividend but that the dividend does not move instantly to a shock in price, that is,

$$
\sigma_{dp} = \sigma_{dp} \quad (4.19)
$$

$$
\sigma_{pp} = \sigma_{pp} - b_{pp} \sigma_{pp} \quad (4.20)
$$

Therefore, suppose the decomposition matrix is set as, $\Sigma_p = LL^t$, where $L$ is a lower triangular matrix with non-zero diagonal elements. The transformed innovation is then expressed as $v_e = L^{-1}e$ and $\text{var}(v_e) = L^{-1} \Sigma_p L^{-1}t = I_d$, where the elements of $v_e$ are uncorrelated random variables and will be referred to “orthogonalized innovations.” The MAR of the VAR($p$) process $\gamma_p$ in terms of $v_e$ is then,

$$
\gamma_p = \Phi(1)c + \sum_{j=1}^{\infty} \Phi_j L v_{1-j} = \Phi(1)c + \sum_{j=n}^{\infty} \Theta_j v_{1-j},
$$

where $\Theta_j = \Phi_j L$ are transformed coefficient matrices. Therefore, the IRF can be calculated from these matrices.

Next, the variance decomposition is usually mentioned in the analysis of the VAR model. The (forecast error) Variance Decomposition (VD) is defined as the fraction of the $k$-step ahead forecast error variance of the $i$-th series accounting for the shock of its own innovations ($i$-th series) and innovations in the other $j$-th series. The
VD is used to show the relative importance of shocks in each equation to variation in a specific series. The VD is also computed using the MAR. Suppose the forecast error is defined as the difference between the actual and forecast value of $Y_{t+1}$, that is,

$$e_{t+1} = Y_{t+1} - E_t Y_{t+1} = \psi_0 e_t,$$  

(4.22)

and its variance is calculated as,

$$Var_t e_{t+1} = \psi_{pp,0}^2 + \psi_{dd,0}^2.$$  

(4.23)

The one-step ahead forecast error variance of price can be separated into two parts due to a price shock ($\psi_{pp,0}^2$) and a dividend shock ($\psi_{dd,0}^2$). To scale the size of each component, the VD is usually reported in fractions of total variance, $\psi_{pp,0}^2/\left(\psi_{pp,0}^2 + \psi_{dd,0}^2\right)$. For the general form of VAR, the VD is generally written as

$$Var_t (Y_{t+1}) = \psi_0' \psi_0.'$$  

(4.24)

Next, let

$$I_2 = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \text{ and } I_2 = \begin{pmatrix} 0 & 0 \\ 1 & 1 \end{pmatrix},$$  

(4.25)

then, the part of the one step ahead forecast error variance due to the first shock $x$ is $\psi_0' I_2 \psi_0'$ while the part due to the second shock $z$ is $\psi_0' I_2 \psi_0'$. Generalizing to k-step can be expressed as follows;

$$Var_t (Y_{t+k}) = \sum_{j=0}^{k-1} \psi_j' \psi_j.'$$  

(4.26)

Then,

$$w_{kt} = \sum_{j=0}^{k-1} \psi_j' \psi_j'.$$  

(4.27)

is the variance of the $k$-step ahead forecast errors due to the $t$-th shock and the variance is the sum of these components, e.g. $Var_t (Y_{t+k}) = \sum_t w_{kt}.$

In sum, the results of the VD in this chapter provide information of the source of the variation in prices and dividends, which can be used as supportive evidence for predictability of either stock returns or dividend growth.
4.4 Empirical Results

4.4.1 Data

In this chapter, the dataset still consists of the aggregate monthly closing stock prices ($P$) and the aggregate monthly dividend-price ratio ($DP$) from the Stock Exchange of Thailand index (SET index). The monthly data were obtained from the Stock Exchange of Thailand and cover the period from April, 1975 to December, 2010. All data were transformed into logarithm form, where log of price ($p_t$), log of dividend ($d_t$) and log of dividend price ratio ($dp_t$) are defined as:

$$p_t = \ln P_t, \quad d_t = \ln(DP_t), \quad dp_t = \ln(DP_t*P_t).$$

Tables 2.1 and 2.2 in Chapter 2 provide the descriptive statistics and stationary property of each series. In summary, the log of prices and log dividends are non-stationary in level but stationary in first differences (return, dividend growth), i.e. $p_t$ and $d_t$ follow the $I(1)$ process. In addition, the log of dividend-price ratio is stationary in level with structural breaks using the ZA test. In addition, the results of the Gregory-Hansen and Bai-Perron tests in Chapters 2 and 3 show that the relationship between price ($p_t$) and dividend ($d_t$) has one structural break in October, 1986.

4.4.2 The VAR Model of the Present Value Model of Stock Price

The empirical investigation in this chapter begins from an estimation of the VAR model with stock prices and dividends as endogenous variables, i.e. $Y=[p, d]$. The number of lag is set using Akaike Information Criteria (AIC). Using AIC criteria, the VAR with three lagged variables was chosen. The constant term was included as deterministic components. The identification of MAR was done using Cholesky decomposition. Dividend was ordered first, followed by prices as suggested by Cochrane (1994). Therefore, the dividend does not response contemporaneously to a shock in price. The IRFs and VDs were then computed for the period up to 60 months (5 years). This length was set to correspond to that of the predictive horizon used in the predictive regressions.

The IRFs from the estimated VAR model, which display dynamic paths of the endogenous variables in the system following a one-time shock to one of the shocks, is firstly considered. The responses of both dividends and prices to the shocks in each equation are presented in Figure 4.1. In addition, variance decomposition was also computed. The results are displayed in Table 4.1.
The results show that both prices and dividends are inclined to move in the same direction as an innovation in the others. Considering a price response, the size of a response to its own shock tends to increase during the first six months and slowly decay after that. After 5 years (60 months), the impact of a shock will decrease by about 28 percent. In addition, the price response to a shock in dividend is very persistent because only 6 percent of the effects of an intitial stock are dissipated after 5 years. Considering the size of response, a rise in dividend provides a much smaller impact on prices than the initial size of the dividend shock. In term of a dividend response to its own shock, the pattern of the IRF is similar to that of a price counterpart. However, dividends tend to be less persistent compared to that of prices as an effect of impulse decline at about 57 percent after 5 years. Lastly, the IRF of the dividend to a price shock shows that, during first six months, dividends tend to move in the opposite direction of a price shock and then inverse to a similar direction of a price shock after six months, and there is no evidence of the mean reversing for a dividend response to an innovation in price.

For the VD, in the short-term (1 years), the forecast error variance of price can be explained by a variance in the dividend by about 6 percent, but the dividend variation does not seem to be related to price (0.4 percent). However, in the long-term (5 years), dividends tend to better explain price variation (15 percent) than prices explain variation in dividend (5 percent). In summary, the estimated results of the IRF and VD show that dividends do not follow a random walk process, while prices do not behave as a mean-reversion process and only small part of the movement is predictable. The empirical evidence also suggests that predictability of dividend growth is more obvious than that of the return using a full sample of data.
Figure 4.1 Impulse Response Functions from the VAR Model of Prices and Dividend Using the Whole Sample Data (April, 1975 to December, 2010)

Note: The Impulse Response was Done Using the Cholesky Decomposition with the Dividend Rank First in the Cholesky Ordering.

Table 4.1 Variance Decomposition from the VAR Model of Prices and Dividend Using the Whole Sample Data (April, 1975 to December 2010)

<table>
<thead>
<tr>
<th>Forecast Horizon (Years)</th>
<th>Log of Price</th>
<th>Log of Dividend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>93.892</td>
<td>6.108</td>
</tr>
<tr>
<td>2</td>
<td>93.842</td>
<td>6.158</td>
</tr>
<tr>
<td>3</td>
<td>94.017</td>
<td>5.983</td>
</tr>
<tr>
<td>4</td>
<td>94.201</td>
<td>5.799</td>
</tr>
<tr>
<td>5</td>
<td>94.361</td>
<td>5.639</td>
</tr>
</tbody>
</table>
### Table 4.1 (Continued)

**Panel (b) Variation in Dividend Variable**

<table>
<thead>
<tr>
<th>Forecast Horizon (Years)</th>
<th>Log of Price</th>
<th>Log of Dividend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.399</td>
<td>99.601</td>
</tr>
<tr>
<td>2</td>
<td>2.622</td>
<td>97.378</td>
</tr>
<tr>
<td>3</td>
<td>6.328</td>
<td>93.672</td>
</tr>
<tr>
<td>4</td>
<td>10.678</td>
<td>89.322</td>
</tr>
<tr>
<td>5</td>
<td>15.055</td>
<td>84.945</td>
</tr>
</tbody>
</table>

**Note:** The Variance Decomposition was Done Using the Cholesky Decomposition with the Dividend Rank First in the Cholesky Ordering.

After that, the results from the sub-sample are considered. In Chapters 2 and 3, evidence of a structural break in long-run relationship between prices and dividends was found. The breakdate was estimated to take place during October, 1986. The results of the predictive regression improved after controlling for the effects of the structural breaks. Therefore, the VAR models were re-estimated by seperating the dataset into two sub-samples, i.e. pre-break (April, 1975 to October, 1986) and post-break (November, 1986 to December, 2010) sub-samples. The number of lagged of endogeneous variables was determined using the AIC. The results show that the optimal number of lags is equal to one and two lags for the VAR models in the pre- and post-break sub-sample, respectively. The IRFs were generated and were displayed in Figure 4.2. The results of the VDs in both the price and dividend series were also computed and were shown in Table 4.2.

Considering the results from pre-break sub-sample, the IRFs of the price response to its own shock show that the series was much less presistent than that of the full sample. In the pre-break sample, the effects of a shock begin to decrease after 2 years and completely vanish after four and a half years. In the post-break sample, this price response started to disipatte after 6 months, which was quicker than that of
the pre-sample and majority (77 percent) of the impact of shock dried out after 3 years. After 5 years, 81 percent of the effect of shock vanished. However, the responses of prices to an innovation in the dividend series were different between the pre- and post-break periods. In the pre-break sub-sample, prices tended to move in the opposite direction to a shock in dividend, which provided a contrast sign to that suggested by the present value model of the stock price. However, a dividend shock led to a permanent shift in prices in the same direction during the post-break period.
Figure 4.2 Impulse Response Functions from the VAR Model of Prices and Dividends Using the Sub-Sample Data

Note: The Identification of the Impulse Response was Done Using the Cholesky Decomposition with a Dividend Rank First in the Cholesky Ordering.
For the dividend series, the results of the IRFs from the pre-break sub-sample show that the impacts of a shock to its own innovation decrease over time and the dividend will decrease from the initial level after 2 years. However, the dividend series responded in the same direction to a price shock and most of the effect dissipated after 5 years, which suggests a mean-reversion property. In the post-break sub-sample, the pattern of response in dividends to both types of shocks was similar to that of the full sample. A positive price shock led to a positive permanent shift in dividend but the magnitude of change in dividend was only about 30 percent of a price shock’s size. A response in its own of dividend also exhibited a higher degree of persistence. About 65 percent of the effects of the shock in a dividend still had not disappeared after 5 years.

Table 4.2 Variance Decomposition from the VAR Model of Prices and Dividends Using the Pre-Break Sub-Sample Data (April, 1975 to October, 1986)

Panel (a) Variation in Price Variable

<table>
<thead>
<tr>
<th>Forecast Horizon (Years)</th>
<th>Log of Price</th>
<th>Log of Dividend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92.609</td>
<td>7.391</td>
</tr>
<tr>
<td>2</td>
<td>72.578</td>
<td>27.422</td>
</tr>
<tr>
<td>3</td>
<td>59.956</td>
<td>40.044</td>
</tr>
<tr>
<td>4</td>
<td>58.529</td>
<td>41.471</td>
</tr>
<tr>
<td>5</td>
<td>60.052</td>
<td>39.948</td>
</tr>
</tbody>
</table>

Panel (b) Variation in Dividend Variable

<table>
<thead>
<tr>
<th>Forecast Horizon (Years)</th>
<th>Log of Price</th>
<th>Log of Dividend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17.279</td>
<td>82.721</td>
</tr>
<tr>
<td>2</td>
<td>45.073</td>
<td>54.927</td>
</tr>
<tr>
<td>3</td>
<td>48.506</td>
<td>51.494</td>
</tr>
<tr>
<td>4</td>
<td>43.896</td>
<td>56.104</td>
</tr>
<tr>
<td>5</td>
<td>43.113</td>
<td>56.887</td>
</tr>
</tbody>
</table>

Note: The Identification of the Variance Decomposition was Done Using the Cholesky Decomposition with a Dividend Rank First in the Cholesky Ordering.
Considering the results of the VD, the majority of variation in prices was explained by its own innovations. This value was also higher in the post-break sub-sample’s results (67 percent at 5-year horizon) than those of the pre-break sub-sample (60 percent at a 5-year horizon). For the dividend series, in the pre-break sub-sample, 51 percent of the variances was due to its own shock at a 5-year horizon. After the break, most of the variation in dividend (91 percent at a 5-year horizon) was explained by its own shock.

Table 4.3  Variance Decomposition from the VAR Model of Prices and Dividends
Using the Post-Break Sub-Sample Data (November, 1986 to December, 2010)

<table>
<thead>
<tr>
<th>Panel (a) Variation in Price Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast Horizon (Years)</td>
</tr>
<tr>
<td>----------------------------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel (b) Variation in Dividend Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast Horizon (Years)</td>
</tr>
<tr>
<td>----------------------------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>

Note: The Identification of the Variance Decomposition was Done Using the Cholesky Decomposition with a Dividend Rank First in the Cholesky Ordering.
These results suggest that, in the post-break period, a dividend series behaves like a random walk process and price looks like a mean-reversion process. The effect of a shock in price is temporary, while the effect of a dividend shock is permanent. In addition, about half of the variation in price can be explained by its own shock. Therefore, the hypothesis that stock price is predictable is more obvious in the post-break sub-sample than in the pre-break period or in the whole sample. These results are similar to those of Cochrane (1994). The only different is that dividends also respond to a price shock in Thailand; however, the size of this effect is marginal. In addition, price response does still not completely disappear. About 20 percent of the effects of shocks are permanent. In the case of the US stock market, Cochrane (1994) find that there is no change in dividends after a price shock and the price response is completely dissipated. Nevertheless, in the pre-break period, the results are not consistent with the present value model of stock price in many aspects. As documented by Crowder and Wohar (1998), estimating the VAR model maybe miss-specified if there is an error-correction mechanism between prices and dividend. Therefore, in the next section, the VECM are further explored.

4.4.3 The VECM Estimation

In this section, the IRFs and VDs are re-estimated using the VECM. In Chapter 2, the results of Johansen’s likelihood ratio rank test showed that the hypothesis of no cointegrating vector could not be rejected. Therefore, the VECM cannot be estimated. However, the Gregory-Hansen test shows that after accounting for structural change, evidence of cointegration is significant. Hence, the VAR model is estimated with an addition of a dummy variable (D1) that represents a break that occurred in October, 1986. Later on, the Johansen test is performed and the results are reported in Table 4.4.
Table 4.4  Johansen’s Cointegration Test (with Dummy Variable to Represent the Structural Break)

<table>
<thead>
<tr>
<th>H₀</th>
<th>Test Statistic</th>
<th>95% Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trace</td>
<td>Max. Eigen value</td>
</tr>
<tr>
<td>r = 0</td>
<td>23.385</td>
<td>18.602</td>
</tr>
<tr>
<td>r ≤ 1</td>
<td>4.784</td>
<td>4.784</td>
</tr>
</tbody>
</table>

Note: r is the Number of Linearly Independent Cointegrating Vectors.

The results in Table 4.4 suggest that there is one cointegrating vector at a 10 percent significant level in the endogeneous sytem of $Y=(p, d)$. The normalized cointegrating vector ($β$) was equal to (1, -0.62). The magnitude of the cointegrating vector was close to that estimated using the Gregory-Hansen method in Chapter 2 (0.53). In the VECM framework, the hypothesis concerning the size of the long-term relationship was tested using the likelihood ratio test. The hypothesis that a long-run relationship between price and dividend existed at (1, -1) cointegrating vector, is tested. The likelihood ratio test statistic was 4.363 and correponding $p$-value was 0.038. Therefore, the null was rejected at a 5% significant level and the dividend-price ratio did not represent long-term disequilibrium value (error-correction term). This result also supports the use of a disequilibrium error as a predictor rather than a (nonstationary) dividend price-ratio, as mentioned in Chapter 3.
Figure 4.3  Impulse Response Functions from the VECM Model of Prices and Dividend.

Note: The Identification of the Impulse Response was Done Using Cholesky Decomposition with the Dividend Rank First in the Cholesky Ordering.

Table 4.5  Variance Decomposition from the VECM Model of Prices and Dividends Using the Whole Sample Data (April, 1975 to December 2010)

<table>
<thead>
<tr>
<th>Panel (a) Variation in Price Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast Horizon (Years)</td>
</tr>
<tr>
<td>--------------------------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>
Table 4.5 (Continued)

Panel (b) Variation in Dividend Variable

<table>
<thead>
<tr>
<th>Forecast Horizon (Years)</th>
<th>Log of Price</th>
<th>Log of Dividend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.225</td>
<td>96.775</td>
</tr>
<tr>
<td>2</td>
<td>9.162</td>
<td>90.838</td>
</tr>
<tr>
<td>3</td>
<td>12.502</td>
<td>87.498</td>
</tr>
<tr>
<td>4</td>
<td>14.244</td>
<td>85.756</td>
</tr>
<tr>
<td>5</td>
<td>15.267</td>
<td>84.733</td>
</tr>
</tbody>
</table>

Notes: The Identification of the Impulse Response was Done Using Cholesky Decomposition with the Dividend Rank First in the Cholesky Ordering. The Dummy Variable Represented the Structural Break in October, 1986 and was Included as the Exogenous Variable.

Therefore, the VECM is estimated without imposing a restriction on the coefficients of cointegrating vector. The error-correction coefficients for both price and dividend equations were equal to -0.049 and 0.022, respectively. Moreover, the results showed that the speed of the prices response to disequilibrium, which occurs from shock in either price and dividend series, was at rate of 4.9 percent per month. This speed of adjustment was quicker than that of the dividend series (2.2 percent per months). Next, The IRFs and VDs are calculated and the results are showed in Figure 4.3 and Table 4.5.
The results from the IRFs show that a dividend shock provides permanent effects on both prices and the dividend itself. Both prices and dividends increase with a positive shock in dividend and take around 6 to 12 months to reach the full effect. I normalized the size of the shock in the dividend. A one percent shock in dividends led to around a 0.62 percent change in prices. This value was close that of the cointegration coefficient (0.57). A price shock provides a temporary impact on its own variables. Most effects (62 percents) of a shock decay during the first three years and are constant after that. Moreover, the half-life of effects of a price shock is approximately 22 months. Most of the remaining impacts (36 percent) were explained by the size of the response to the dividend from a price shock.
Table 4.6 Variance Decomposition from the VECM Model of Prices and Dividends with the Price Rank First in the Cholesky Ordering

<table>
<thead>
<tr>
<th>Panel (a) Variation in Price Variable</th>
<th>Forecast Horizon (Years)</th>
<th>Log of Price</th>
<th>Log of Dividend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>94.566</td>
<td>5.434</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>85.810</td>
<td>14.190</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>75.066</td>
<td>24.934</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>66.955</td>
<td>33.045</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>61.402</td>
<td>38.598</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel (b) Variation in Dividend Variable</th>
<th>Forecast Horizon (Years)</th>
<th>Log of Price</th>
<th>Log of Dividend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>11.219</td>
<td>88.781</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>20.788</td>
<td>79.212</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>25.591</td>
<td>74.409</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>28.056</td>
<td>71.945</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>29.501</td>
<td>70.499</td>
</tr>
</tbody>
</table>

Note: The Estimation of the VECM is Similar to That of the Results in Table 4.5 but Cholesky Decomposition is Done with the Price Rank First in the Cholesky Ordering.

Furthermore, the VD results show that a majority of the variation in the price and dividend series in 5 years can be explained by its own innovation. Price shocks account for about 75 and 66 percent of its own forecast error variance at a three- and five-year horizon, while the remaining parts of the forecast error variance were attributed to dividend shocks. For the dividend series, most of its variation (87 percent and 85 percent during 3 and 5 years, respectively) was explained by its own
innovation. These results are similar to those of the VAR model using the post-break sub-sample.

Next, the sensitivity of results of IRFs and VDs to the Chalosky ordering was examined. The IRFs and VDs from the VECM Model were re-calculated with the price rank first in the Cholesky ordering. This order implies that the price does not response contemporaneously to a shock in dividend. The results of the IRFs and VDs are shown in Figure 4.4 and Table 4.6, respectively.

Overall, the results from the IRFs and VDs from Figure 4.4 and Table 4.6 pointed out that the patterns of both prices and dividend response are similar to those of Figure 4.3 and Table 4.5. However, the results from the VDs showed that variations in the dividend due to a shock in price were higher by about 10 percents in every forecast horizon. Hereafter, the smaller portion (50 percents) of the effects of a shock decay during the first three years.

Lastly, the significance of the direction of relationship between the prices and dividends series is investigated using the Granger-Causality test. In the VECM, the causality tests can be done using the block exogeneity Wald tests. For each equation in the VAR, the Wald tests for the joint significance of each of the other lagged endogenous variables in that equation are computed and the results are shown in Table 4.7.

**Table 4.7** The Granger Causality Tests for the Direction of Relationship between the Prices and Dividends Series in the VECM

<table>
<thead>
<tr>
<th>The Null Hypothesis</th>
<th>Chi-Square Statistics</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dividends do not Granger cause prices</td>
<td>12.62</td>
<td>0.082</td>
</tr>
<tr>
<td>Prices do not Granger cause dividends</td>
<td>9.99</td>
<td>0.189</td>
</tr>
</tbody>
</table>

**Note:** The Wald Test Statistics and Their P-values are Reported for Testing the Null Hypothesis That the Price Coefficients are Jointly Equal to Zero in the Dividend Equation of the VECM and Vice Versa.
First, the Wald test is performed for the price equation. The results from Table 4.7 show that the coefficients on the lagged variables of the dividend series were significantly different from zero at 90 percent confidence level as the \( p \)-value was equal to 0.082. For the dividend equation, the \( p \)-value was 0.189. This implied that the null hypothesis that the price does not Granger cause the dividend could not be rejected. In other words, the effect of a change in the price to the dividend movement was not significant. Therefore, the uni-directional Granger causality from the dividend to the price was found. These results support the findings in the IRFs and VDs, which were discussed in Section 4.4.2.

### 4.4.4 The Structural VECM Estimation

To further investigate the issue of the permanent and temporary component in stock price, the Structural VAR (SVAR) approach with Blanchard and Quah’s (1989) decomposition is used. This model is used to generate the IRFs when a dividend shock is set to be permanent and a price shock had only a transitory effect. The IRFs generated from the SVAR approach are used to compare those of the VAR and VECM to investigate the issue of the permanent and transitory component in stock price. A brief description of the methodology of the SVAR model is explained as follows.

Consider the the structural form of the VAR model. The standard form of the SVAR model is written as follows.

\[
A_l^c Y_t = A_1^c Y_{t-1} + \cdots + A_p^c Y_{t-p} + B \varepsilon_t
\]

(4.28)

There are two alternative approaches to identifying the structural of relationship under the SVAR framework. First, the structure of contemporaneous relationship in the system could be defined in a vector of endogenous variable, \( Y_t \) (A matrix), in a vector of structural error terms, \( \varepsilon_t \) (B matrix), or both. Therefore, this approach is usually refered to as the AB model. The second approach proposed by Blanchard and Quah (1989) uses a restriction concerning the long-run effect of shocks on identifying the model. This approach assumes that shocks in some variables will provide a permanent impact, while shocks in the other variables have only a temporary effect. Therefore, the Blanchard-Quah model focuses on the MAR of the VAR model. Then, the “A” matrix was set to be an identity matrix (\( I_k \)). The matrix of
the long-run effect \((I_d - A_2 - \cdots - A_p)^{-1}B\) was assumed to be lower triangular. Therefore, in the bivariate system, a shock in the first variable has a long-run (permanent) impact on its own series and second series. However, the second residual does not have a permanent (long-term) impact on the first variables. Therefore, a shock in the second variable has a transitory effect on the system. The Blanchard-Quah approach can be extended to the Sturttural Vector Error Correctoin Model (SVECM) by imposing restrictions on the matrix of the long-run effects of shocks similar to that of the SVAR model. (see Lutkepohl and Kratzig, 2008: 37-38 for details on the estimation of SVECM with Blanchard-Quah’s restrictions)

In the case of the bivariate model of prices and dividend, Cochrane (1994) suggests that the effect of a dividend shock should be treated as a permanent effect, while a price shock provides a transitory component. He also derives the property of the bivariate VAR model of prices and dividends. In addition, he shows that when a price shock has a temporary effect and a dividend shock has a permanent effect, the results of the IRFs calculated using Cholesky decompotion with dividend order first will similar to those computed by the Blanchard-Quah decompostion. Cochrane (1994) also provides empirical results from the U.S. stock market that supported this hypothesis. Therefore, the Blanchard and Quah decompostion is applied in both bivariate VAR and VECM of prices and dividends. The IRFs are computed and the results are shown in Figure 4.5

Comparing the IRFs from the SVAR model in Figure 4.5: panel (a) with those of the VAR model in Figure 4.1, it can be seen that the IRFs provide a similar pattern that a dividend shock has a permanent impact on price and overshooting of the price change is found during the first six months. Considering the effect of a price shock, this effect was completely disappeared in the SVAR. However, in the VAR model, the prices did not decline to the original level before a shock. In addition, the dividend response was also different in the VAR and VECM. In the SVAR model, the IRFs showed that the dividend was initially response in opposite direction to a price shock and gradual decay toward zero. For the IRFs of the VAR model, the negative impact was quickly corrected and the dividend exhibited a long-term positive shift followed by a price shock.
Panel (a) SVAR Model

Panel (b) SVECM

Figure 4.5 Impulse Response Functions from the SVAR Model and SVECM of Prices and Dividend with Blanchard-Quah Decomposition

Notes: The Estimation of the SVAR and SVECM in This Section is an Extension of the VAR Model Used in the Computation of IRFs in Figure 4.1 (section 4.4.2) and the VECM Used in the Calculation of the IRFs in Figure 4.3 (section 4.4.3).
The results of the IRFs from SVECM of Figure 4.5: panel (b) and IRFs from the VECM in Figure 4.3 show that only the dividend responses to its own shock. Moreover, a similar pattern between the results from the VECM and SVECM were found. The dividend looks like a random walk process where the effect of a shock is permanent. For the dividend response to a price shock, initial negative responses were still found in the IRFs from both the VECM and SVECM models. However, the VECM results show that the dividend also permanently increased with a price shock, which is similar to those of the VAR and SVAR models. Because the Blanchard-Quah decomposition restricts the long-run impact approach to zero, the magnitude of the negative response in the SVECM was amplified. Even though a dividend shock seemed to have a permanent effect on the IRFs from both the VECM and SVECM model, the price responses to a dividend shock seemed to over-react in the first two years in the SVECM results. However, this overshooting pattern was not found in the VECM results. For the price response, the effects of its own shock in the price series did not completely dissipate in the VECM results. This pattern can be explained by the permanent dividend reaction to a price shock.

From the above results, imposing the Blanchard-Quah decomposition to the VAR and VECM provides the results that are not consistent with those of the models without restriction. Therefore, both the SVAR and SVECM with the Blanchard-Quah decomposition are not suitable for the data in Thailand.

4.5 Conclusion

In this chapter, the analysis of the present value model of stock prices is extended to the VAR framework. Several systems of the VAR, VECM, SVAR, SVECM were estimated. The IRFs, VDs and Granger causality tests were calculated to provide information about the relationship between stock prices and dividends. The results provide further information about the reaction pattern in both prices and dividends to shocks in the system. The empirical results from Cochrane (1994) and Crowder and Wohar (1998) show that shocks in stock prices provide a transitory effect, while the effects of shocks in the dividend are permanent. Cochrane (1994, 2011) explains that a pure price shock in the VAR system of the present value model
of stock price can be interpreted as a change in the discount rate. Therefore, he suggested that these results provide supportive evidence of return predictability.

Using the IRFs and VDs estimated from the VAR, VECM, SVAR, SVECM systems, the empirical results from the VECM showed that there are the mean-reversion pattern in the price series and the random walk pattern in the dividend series. However, there are some differences between the results of the Stock Exchange of Thailand in this chapter and those of the US market reported in Cochrane (1994) and Crowder and Wohar (1998). Specifically, in the case of Thailand, a price shock also provides a permanent impact on dividend; however, the size of dividend response is much smaller than the size of a price shock. Therefore, the stock price response to its own shock is not completely disappeared. In particular, about 70 percent of the effect of shock is temporary and the remaining 30 percent is permanent. Furthermore, the SVAR and SVECM with the Blanchard-Quah decompostion are not suitable for the data in Thailand. The stock price series cannot be treated as a stationary process. However, the VD results show that majority of parts in the variation in price could be attributed to its own shocks. Therefore, return predictibility is still supported but the results are not as strong as those of the US market. In addition, dividend growth also contains predictability power because dividends also respond to a price shock. However, the predictability in dividends should be weaker than that of prices. These results support the finding of a predictive regression in Chapter 3.

In summary, dividend movement seems to follow the random walk process but it also responds to a shock in price as well as its own innovation. As a result, the effect of a price shock is not completely temporary. An over-reaction pattern of a price response to dividend news is also found.
CHAPTER 5

CONCLUSIONS AND IMPLICATIONS

5.1 Conclusions

In this dissertation, the predictability of stock returns using the dividend price ratio was investigated using the monthly data from the Stock Exchange of Thailand from 1975:04 to 2010:12. In the modern financial theory, stock returns predictability is linked to time-varying expected returns. Specifically, investors demand higher expected returns during a bad economic period in order to compensate for the holding of high-risk assets. The derivation of the present value model of stock prices under time-varying expected returns reveals that the predictability of stock returns is possible and does not invalidate the Efficient Market Hypothesis. In particular, the one-period stock returns predictive regression can be expressed as follows:

\[ R_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1}, \]  

while the expected returns at time \( t \) are referred to by the following equation:

\[ E_t(R_{t+1}) = \alpha + \beta x_t. \]  

The significance of \( \beta \) from equation (5.1) implies that the stated variable, dividend-price ratio in particular, is able to explain the variation in one-period stock returns. In addition, the significance of \( \beta \) from equation (5.1) and (5.2) reveals that the expected returns are not constant over time. Even though, the expected returns were not directly observed, theory suggests that the dividend-price ratio is able to predict long-horizon returns to the degree that reflects the movements in the unobservable expected returns. Therefore, the test of stock returns predictive regression is equivalent to the test of time-varying expected returns. To be more specific, the predictive content of the dividend-price ratio is due to its tendency to proxy the expected returns over the business cycle (Fama and French, 1989). As a
consequence, the stock returns predictive regression was examined rather than expected returns regression.

This dissertation began by testing for cointegration relationship between stock prices and dividends in Chapter 2. The present value model of stock prices (Campbell and Shiller, 1987, 1988) suggests the existence of the long run relationship between prices and dividends. Surprisingly, the structural change in the cointegrating coefficient was found and the log of the stock prices and log of dividends did not exhibit a cointegrating coefficient (1,1). Moreover, the formal structural break test in Chapter 3 strongly confirmed the existence of structural change in the mean of dividend-price ratio. In sum, simply using the dividend-price ratio as a predictor in equation (5.1) may invalidate the results since its properties do not satisfy classical linear regression assumptions. As a result, proper methods in data transformation were used and then returns predictive performances were evaluated.

A structural break is possible when a long-span dataset is used in the research. In this dissertation, Bai and Perron’s (1998) test was performed to estimate the numbers of unknown breaks as well as to locate the break dates. In particular, there was one shift in the mean of the dividend-price ratio and the corresponding break date was October, 1986. The economic explanation of such structural change is due to two possible issues. One is the increasing role of foreign investors, while another is the growing numbers of listed firms.

The Stock Exchange of Thailand was set up in 1975 with the aim to support and promote the economic growth and stability, and to provide more trading stock channels for both investors and find-raisers. Practically speaking, the Stock Exchange of Thailand was in “the developing period” during the first decade, 1975 - 1986. At that time, the Thai economy was very volatile, as oil prices and interest rates were high. Private savings were less than the demand for investment; moreover, the political situation was unstable due to the political situation of the neighboring countries. Even through the primary objective of the stock market was to facilitate capital allocation and to enhance capital fund flows, the investment environment was not attractive and did not promote trading activities from foreign investors as expected. However, after this period, the Stock Exchange of Thailand developed and set up standard trading regulations and began promoting an open economy. Together
with the stability of the political situation, the flows of foreign investment had begun to rise according to the stock market liberalization in September, 1987 (Bekaert and Harvey, 2000).

Overtime, Thailand has been reducing the investment barrier for foreign investor. According to Huang and Yang (2000) who study about the foreign investment in Thailand, they classify foreign investment into two categories: long-term investment or foreign direct investment (FDI) and short-term investment or portfolio investment (PI). They also note that Thailand’s foreign investment is dominated by short money invested in capital market. Overtime, the foreign investment would be restricted by the foreign shareholders’ or investments’ limitation. However, foreign investors were allowed to hold shares up to 49 percent of the total in a Thai company since December, 1988. Figure 5.1 shows the soaring of foreign portfolio investment from less than a thousand million dollars to more than 2,000 million dollars beginning in 1987. This also made the ratio of foreign investment in the stock market swell from 4 - 5 percent in 1986 to 14.40 percent in 1990. (Panit Kerdchokchai and Boonlarb Phusuwan, 2005).

In addition, Figure 5.2 discloses the numbers of listed firms that have continuously increase—from 98 firms in 1986 to hundreds later on. In addition, according to the government policy to promote investment or the financial liberalization, Figure 5.3 also shows that the trading values have increased 4 - 5 times and the SET index doubled over the year. Meanwhile, Thailand’s economy expanded at an average pace of 9 percent per annum during 1987–1996. According to World Bank (1997), during such period, Thailand received very large and sustained inflows of foreign capital, averaging some 9.4 percent of GDP per annum.
Figure 5.1  Foreign Portfolio Investment in Thailand (1975 - 2010), Unit: Million USD

Figure 5.2  Numbers of Listed Firms on the Stock Exchange of Thailand (1975 -2010)
Structural breaks manifest themselves in the time series data for a number of reasons for instance economic crises, policy changes and regime shifts. Interestingly, the test results show that there was no structural break in 1997\(^1\) (Yuthana Sethapramote and Suthawan Prukumpai, 2012) Even though it is widely accepted that the Asian financial crisis originated in Thailand and created a ripple effect throughout the region, the Bai and Perron test statistics do not provide any evidence of a structural break during that time. In conclusion, the empirical analysis in this dissertation reveals that, over the sample period of 1975:04 to 2010:12, the structural changes in the dividend-price ratio in Thailand were more likely to have been a consequence of policy and regulatory change rather than economic crisis.

It is clear that there was a structural break in the predictor, the dividend-price ratio in particular, which violates the assumptions of the standard linear regression and also invalidates the statistical inference. According to the extant literature, there are two alternatives in dealing with this problem. One is to find the asymptotic

\(^1\) Examine the time variation and structural break in return volatility in the Stock Exchange of Thailand during 1975-2010. They find two structural breaks in the mean of conditional return volatility. However, such breaks do not locate around Asian Financial Crisis. Their results are similar to that of Kim, Seo, and Leatham (2010).
distribution of estimated parameters using the bootstrapping method. Another is to use the transformed variable. The latter method was chosen in this dissertation and the predictive regression results were summarized in Chapter 3. Specifically, the disequilibrium error from the cointegration regression and the adjusted dividend-price ratio according to Lattua and Nieuwerburgh’s (2008) framework were used. Overall, there are two main findings regarding the returns predictive regression. First, predictability using the transformed dividend-price ratio improved. Second, the transformed dividend-price ratio predicted returns better than dividend growth. Even though the results from the return predictive regression are not as strong as expected, the overall results show the importance of structural break information.

The evidence that supports long-horizon stock returns predictability implies that the stock prices do not exhibit a random walk process, but behave as a mean reverting process. Motivated by Cochrane (1994), Chapter 4 extends the study to a multivariate framework using the Vector Autoregression (VAR) model. In this framework, both stock prices and dividends are treated equivalently as endogenous variables. Therefore, the time paths of each variable are concurrently affected by sequences in other variables. The advantages of estimating the regression in the VAR model are not only to provide information about the relationship between prices and dividend, as suggested by the present value model of stock prices, but also to reveal the dynamic responses of both prices and dividends to shocks in each equation through the Impulse Response Function (IRF). In particular, the VAR framework enables the distinction between temporary shocks and permanent shocks. Moreover, if the variable permanently reacts to innovation, such a variable is considered to be a random walk process and that shock is interpreted as a permanent shock since its effect does not dry out over time. On the other hand, if the shock has a temporary effect on the variable, such a variable has a mean reverting process and that shock is considered as a temporary one.

Overall, the empirical results reveal that stock prices have a mean reversion property while dividends have a random walk pattern. Specifically, since dividends are random walk and are not forecastable, if current dividends do not change (no contemporaneous shock on dividends), then expected future dividends do not change either. Unlike dividends, a rise in expected returns, with no change in dividends, must
give lower prices or lower ex-post returns, just as a rise in bond yield must mean a decline in the bond price. In other words, given a price shock with no contemporaneous shock in the dividend, future prices will completely mean reverting process. This confirms the evidence of stock returns predictability in Thailand. Particularly, the dividend-price ratio forecasts returns much more strongly than it forecasts dividend growth, so prices rather than dividends adjust to bring the ratio back to its mean.

The present value model, together with the dividend smoothing hypothesis, (Lintner, 1956; Black, 1976) can be used to interpret the VAR of prices and dividends. Recall the present value model (equation (1.18)), which states that the dividend-price ratio depends on expectations of future discount rates (or expected returns) and dividend growth rates. In addition, the present value-dividend smoothing model suggests that there are two shocks—earnings shock or cash flows shock and discount rate or expected return shock. More specifically, increases in dividends signal a better future prospect as an increase in future cash flows, and if discount rates or expected returns remain constant, stock prices rise simultaneously. Therefore, a dividend shock, which is a cash flow shock, is permanent. Therefore, dividends, following a random walk, remain at the new level, so stock prices also do.

On the other hand, if expected returns or the discount rate decreases without a concurrent change in dividends, prices rise and as expected, returns revert to their mean, and prices also revert. Thus, a discount rate or expected returns shock gives rise to a temporary price change with no change in dividends. Overall, the empirical results in this dissertation support the New Fact in Finance Hypothesis, as proposed by Cochrane (1999), that stock prices do have a mean reversion process and their movement resulted from a discount rate or expected returns shock rather than cash flow shock. Moreover, since the stock returns are predictable rather than dividend growth, the expected returns are time-varying.

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2In the classic study, he finds that dividend-smoothing behavior is widespread since firms are primarily concerned with the stability of dividends.

3An increased dividend causes the stock prices to rise, and conversely for cuts in dividends.
5.2 Implications

The evidence of long-horizon stock returns predictability would provide beneficial information for investor seeking to make sensible portfolio allocation decisions. Specifically, given the evidence of predictability in returns, should a long-horizon investor allocate his or her wealth differently from a short-horizon investor? The classic work of Samuelson (1969) and Merton (1969) show that if asset returns are Independent Identical Distribution (i.i.d.) an investor with a power utility that rebalances his or her portfolio optimally should choose the same asset allocation, regardless of the investment horizon.

However, according to the growing body of evidence that returns are predictable, including that discussed in this dissertation, the investor’s horizon may no longer be irrelevant. Merton (1973) found that variation in expected returns over time can potentially introduce horizon effects. Barberis (2000) carefully examined how the evidence of predictability in asset returns affects the optimal portfolio choice for investors with long horizons. He stated that there is a positive monotonic horizon effect predominates for US stocks. In particular, because of the predictability in returns, the longer the investment horizons, the more funds investors will allocate to stocks. A possible explanation is that if returns are mean reverting, then the variance of total return increases, but it does so at a lower rate than in the i.i.d. case. This implies that stocks can be relatively less risky in the long run, which may lead investors to favor risky assets over long horizons. As a result, he concludes that a risk-averse long-term investor should allocate more to stocks than a short-term investor, consistent with Kritzman and Rich (1998).

In this dissertation, the evidence that stock returns are negatively serially correlated or that a mean reverting process introduces investors the implication of “contrarian strategy” in order to take advantage of time-varying expected returns. Specifically, it is recommended buying low-price stocks (or during bad economic conditions) and holding them for at least three to five years. Since the dividend-price ratio is a proxy of slow, mean-reverting expected returns over the business cycle, the market expectations can be tracked by observing the movement of the dividend-price ratio relative to its long-run mean. In addition, the evidence of stock returns predictability
can benefit the buy-and-hold strategy regarding the horizon effects. Particularly, the mean-reverting property makes stocks appear less risky to long-horizon investors and leads them to allocate more to equities than would investors with shorter horizons. This could be applied to investors that buy either individual stock or a portfolio of stocks, such as the Long-Term equity Fund (LTF) or other types of mutual funds.

Nevertheless, it is important that investors take into account the uncertainty about model parameters such as the coefficient on the predictor. Therefore, it is necessary to adopt a proper framework that is able to incorporate the instability information, i.e. using the transformed dividend-price ratio. Barberis (2000) documents that incorporating parameter uncertainty significantly changes the optimal allocation; however, horizon effects are still present in less prominent. (Merton, 1973; Kim and Omberg, 1996; Kandel and Stambaugh, 1996).

Another implication from stock returns predictability evidence is the recognition of time-varying expected returns or the time-varying discount rate as another risk factor. Specifically, the multiple priced factors are expected and the traditional one-period CAPM is no longer able to explain the variations in asset returns. Regarding the Intertemporal CAPM logic, stated-variable hedging is necessary and multi-period analysis is recommended. For example, suppose you are a highly risk-averse investor, with a 10-year horizon investment in a 10-year zero-coupon indexed Treasury (The example is borrowed from Cochrane, 2011: 1082). Suppose now that bond prices plunge, and volatility surges; should you sell in a panic to avoid the risk of further losses? The answer is no since “short-term volatility” is irrelevant. Likewise, if the stock market plummets during a subprime crisis, you also should not sell in a panic to avoid additional losses.

Lastly, asset pricing theories and applications in practical asset allocation usually assume Independent Identical Distribution returns and rely on the traditional static CAPM. Throughout this dissertation, the evidence of long-horizon stock returns predictability or time-varying expected returns would lead us to refocus the analysis of stock prices and enlarge our understanding about risk factors. Specifically, the

\[ \text{\footnotesize{\textsuperscript{4}}}\text{For examples of empirical work on portfolio choice in the presence of time-varying returns.} \]
\[ \text{\footnotesize{\textsuperscript{5}}}\text{Moreover are the first to point out the importance of recognizing parameter uncertainty in the context of portfolio allocation with predictable returns.} \]
changes in stock prices are due to the changes in the discount rate or expected returns shock rather than changes in expected future cash flows. The Stock returns predictability is a must and it does not violate the Efficient Market Hypothesis. All of these rely on the same underlying reason—that the expected returns are time-varying or the discount rates vary more than thought. However, as mentioned by Cochrane (2011), the facts about time-varying expected returns or discount rate variation are at the beginning stage, and the theories are in their infancy. Thus, comprehensive studies are still under way.


# BIOGRAPHY

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